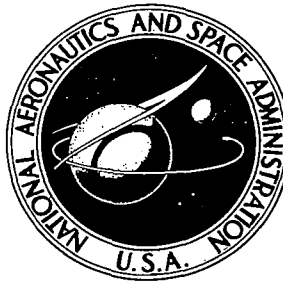


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**A CONTROL-THEORY MODEL
FOR HUMAN DECISION-MAKING**

by William H. Levison and Robert B. Tanner

Prepared by

BOLT BERANEK AND NEWMAN, INC.

Cambridge, Mass. 02138

for Ames Research Center

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16. Abstract A model for human decision-making has been developed and tested against experimental data. This model is a straightforward adaptation of the optimal-control model for pilot/vehicle systems developed by Bolt Beranek and Newman Inc. The models for decision and control both contain the concepts of time delay, observation noise, optimal prediction, and optimal estimation. The model for decision-making developed in this study is intended to apply to situations in which the human bases his decision on his estimate of the state of a linear plant. Experiments are described for the following task situations: (a) single decision tasks, (b) two-decision tasks, and (c) simultaneous manual control and decision-making. Using fixed values for model parameters, we can predict single-task and two-task decision performance to within an accuracy of 10 percent. Agreement is less good for the simultaneous decision and control situation, and the results of this experiment do not allow a conclusive test of the predictive capability of the model in this situation. <div style="text-align: right;"> 1. Decision Making 2. Manual Controls 3. Automatic Control 4. Pilots (personnel) -- Performance </div>			
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SUMMARY

A model for human decision-making has been developed and tested against experimental data. This model is a straightforward adaptation of the optimal-control model for pilot/vehicle systems developed by Bolt Beranek and Newman Inc. The models for decision and control both contain the concepts of time delay, observation noise, optimal prediction, and optimal estimation. The model for decision-making developed in this study is intended to apply to situations in which the human bases his decision on his estimate of the state of a linear plant.

Experiments are described for the following task situations: (a) single decision tasks, (b) two decision tasks, and (c) simultaneous manual control and decision-making. Using fixed values for model parameters, we can predict single-task and two-task decision performance to within an accuracy of 10 percent. Agreement is less good for the simultaneous decision and control situation, and the results of this experiment do not allow a conclusive test of the predictive capability of the model in this situation.

1. INTRODUCTION

Considerable effort has been devoted to understanding how a pilot controls his aircraft, and reasonably accurate models for the pilot as a feedback controller have been developed. Continuous control, however, is but one of the functions required of the pilot; he must also make some crucial decisions during the course of a flight. Perhaps most important is the decision whether to attempt a landing or to go around for another try. Clearly, a miscalculation could have very serious consequences. In addition, the pilot must continuously monitor the behavior of the aircraft so that he may ascertain whether or not the system is behaving properly. Control-system failures will occur from time-to-time, and the pilot must quickly identify such a failure and initiate the appropriate recovery strategy. As flight-control systems become more sophisticated, monitoring and decision-making tasks will play an increasingly important role in the pilot's management of the aircraft.

In order that we may have the proper tools for analyzing modern flight-control systems, models for the pilot must be developed which account for his decision-making as well as his control behavior. If we wish to understand how the pilot performs a multiplicity of decision and control tasks, as he is often required to do, the models for decision behavior must be integrated into the models for monitoring and control. Ideally, a common model structure would be developed to handle all the important tasks required of the pilot and to account for the mutual interference among these tasks that occurs because of the pilot's limited workload capacity.

This report describes a study performed for NASA-Ames Research Center to develop a model for human decision-making that can ultimately be applied to decisions relating to aircraft management. Model development has been guided by the requirement to maintain a common model structure for both decision and control behavior. This work builds logically upon studies of multi-variable manual control systems performed under previous contracts with NASA-Ames.

The model for decision-making developed in this study is intended to apply to situations in which the human bases his decision on his estimate of the state of a linear plant. It is based on the existing optimal-control model for pilot/vehicle systems developed by Bolt Beranek and Newman Inc. The optimal-control model contains the concepts of observation noise, optimal prediction, and optimal estimation which can be directly applied to certain types of decision problems. In addition, the existing pilot/vehicle model is able to account for interference among control tasks performed in parallel. Because the existing model structure appears particularly well-suited for encompassing both decision and control tasks, our efforts have been confined to refining this particular model structure and we have not searched for others which might explain the decision behavior observed in the experimental study.

The report is organized as follows. In Chapter 2 we review existing models for decision-making and control that are relevant to this study. New model development is presented in Chapter 3, along with a description and analysis of the decision task explored in this study. Principal experimental results are presented in Chapter 4 and discussed further in Chapter 5. Concluding remarks appear in Chapter 6. The appendices contain supplemental information relating to the experimental and analytical procedures.

2. CURRENT MODELS FOR CONTROL AND DECISION-MAKING

The model for human decision-making that is presented in this report builds logically upon existing models for human control and decision-making. The observation noise, optimal estimation, and optimal prediction concepts that appear in the optimal-control model for continuous tracking are key elements in the model for decision-making. In order that the reader may follow the model development presented in the next section of this report, we review below the most relevant features of existing models for human control and decision-making.

2.1 Optimal Decision-Making

Models for optimal decision-making are summarized in detail in References 1 and 2. These models are based on the premise that well-trained humans decide in a near optimal manner. That is, decisions are made to maximize (or minimize) some performance measure. A number of performance measures may be postulated, and there has been some controversy in the literature as to which ones are appropriate to various decision situations (Ref.1). We shall consider here the class of decision-making tasks in which it is reasonable to assume that the human attempts to maximize the expected "utility" of the outcome of his decision.

Decisions are almost always based on less than perfect information about the present (or future) "state of the world". The state of the world may be one of any number of mutually exclusive possibilities; the human must determine the probability that each of the potential states is the true state. Two or more courses of action (i.e., "decisions") are possible, the correctness of any decision depending upon what happens to be the true state of the world.

In order to model decision-making in the presence of uncertainty, we pretend that the human adopts the following decision strategy. First, he assigns numerical "utilities" to each of the possible outcomes of each decision. (For example, in deciding whether to land an aircraft or to abort, the pilot should weigh the benefit of making a successful landing, the cost of a crash, and the cost of making a go-around.) Typically, the utility of a correct decision is numerically positive, whereas that of an incorrect decision is negative. Having assigned utilities, the human then calculates the probabilities associated with each of the possible states of the world being true, using whatever relevant information he is able to obtain. He now computes the expected utility associated with each decision and makes the decision that yields the largest expected utility. Decision-making may thus be considered as a three-step procedure: (a) assignment of utilities to each state-decision combination, (b) assessment of the probabilities of the state of the world, and (c) taking the appropriate action.

We shall consider the human's decision task as primarily that of determining the probabilities of the various states of the world. The utility matrix is assumed to be constructed prior to the task^{*}, and the action to be taken is automatic once the expected utilities have been computed.

We now formalize some of the concepts associated with the utility-maximization theory of human decision-making. Let the possible states of the world be represented by a set of mutually-exclusive hypotheses h_1 . One (and only one) of them represents

* Although it is a nontrivial task to determine the appropriate utility matrix in many realistic situations, the experimental tasks explored under this contract involved a utility matrix that was easily understood and accepted by the subjects.

the "true" state. The decision that the i^{th} hypothesis is true is represented by H_i . The utility of deciding H_i when, in fact, h_j is true may be represented as $U(H_i, h_j)$ or, more compactly, U_{ij} . We assume that the U_{ij} are numerically positive for $i=j$ (the set of correct decisions) and negative otherwise.

The human is presented some data $[z]$ on which to base his decision. These data may be discrete items of information, continuous waveforms, or combinations of both. In any case, we use $[z]$ here to represent the entire past history of the data. The expected value of the utility associated with deciding H_i is

$$E\{U|H_i\} = \sum_{j=1}^N U_{ij} \cdot P(h_j|z) \quad (1)$$

where $P(h_j|z)$ is the probability that hypothesis h_j is true, given the available data. The optimal decision strategy is simply to select the hypothesis H_i which maximizes the expected utility.

Many important decision tasks require the human to decide between two possible hypotheses (e.g., a contemplated landing either does or does not have a sufficiently high probability of success). The decision tasks to be studied under this Contract will fall into this class. Accordingly, we analyze the binary decision task in greater detail.

Assume two mutually exclusive hypotheses h_1 and h_0 . The expected utilities of the possible decisions H_1 and H_0 are given as

$$E\{U|H_0\} = U_{00} \cdot P(h_0|z) + U_{01} \cdot P(h_1|z) \quad (2a)$$

$$E\{U|H_1\} = U_{10} \cdot P(h_0|z) + U_{11} \cdot P(h_1|z) \quad (2b)$$

The decision rule is to decide H_1 if the expected utility associated with H_1 is greater than the expected utility associated with H_0 ; otherwise, decide H_0 . Accordingly, we derive the following decision rule from Equations (2a) and (2b):

$$\left. \begin{aligned} H &= H_1 \text{ if } \frac{P(h_1|z)}{P(h_0|z)} > \frac{U_0}{U_1} \\ H &= H_0 \text{ otherwise} \end{aligned} \right\} \quad (3)$$

where $U_0 = U_{00} - U_{10}$ and $U_1 = U_{11} - U_{01}$. The decision rule, then, may be based on the ratio of probabilities (the "odds ratio"), which, it seems, is more reliably estimated by humans than are the individual probabilities (Ref.1).

Computation of the odds ratio is often facilitated by the use of Bayes' theorem, which may be stated as

$$P(h,z) = P(h|z) \cdot P(z) = P(z|h) \cdot P(h) \quad (4)$$

where $P(h,z)$ is the joint probability of the event $[h]$ and the data $[z]$, and $P(z)$ is the overall probability that event $[h]$ will occur. $P(h)$ is often called the "prior probability"; that is, the estimate of the probability that hypothesis $[h]$ is true that is made before the data $[z]$ have become available. Using Equation (4), we may restate the decision rule to be

$$\left. \begin{aligned} H &= H_1 \text{ if } \frac{P(z|h_1)}{P(z|h_0)} > \frac{U_0}{U_1} \cdot \frac{P(h_0)}{P(h_1)} \\ H &= H_0 \text{ otherwise} \end{aligned} \right\} \quad (5)$$

where the ratio $P(z|h_1)/P(z|h_0)$ is called the "likelihood ratio". The optimal (Bayesian) decision rule is usually expressed in this form.

2.2 Models for Continuous Control

2.2.1 The Optimal-Control Model for Pilot-Vehicle Systems

The reader is assumed to be familiar with the optimal-control model that has been developed for analyzing pilot-vehicle systems. This model, which is described in detail in References 3 and 4, has been found capable of reproducing performance measures in a variety of single-variable and multi-variable tracking situations (Refs.5-10). Most of the elements of the optimal-control model are contained in the model for human decision performance presented in the following chapter of this report.

In order to refresh the reader's memory, a block diagram of the model is shown in Figure 1. Let us review briefly those elements which relate directly to human performance (shown within the dashed line). Human limitations are represented by a time delay $[\tau]$, by observation and motor noise processes, and, to some extent, by certain terms in the cost functional. The observation noise process $\underline{v}_y(t)$ accounts for most of the stochastic portion of the human's response (i.e., remnant); in some cases, a separate motor noise term $v_u(t)$ is needed to provide an accurate match to certain aspects of the controller's behavior. A cost weighting on mean-squared control-rate activity is typically included in the cost functional to represent limitations (both physiological and self-imposed) on the bandwidth of the controller's response. The effect of this weighting is to generate a first-order lag with time constant τ_n in the control strategy.

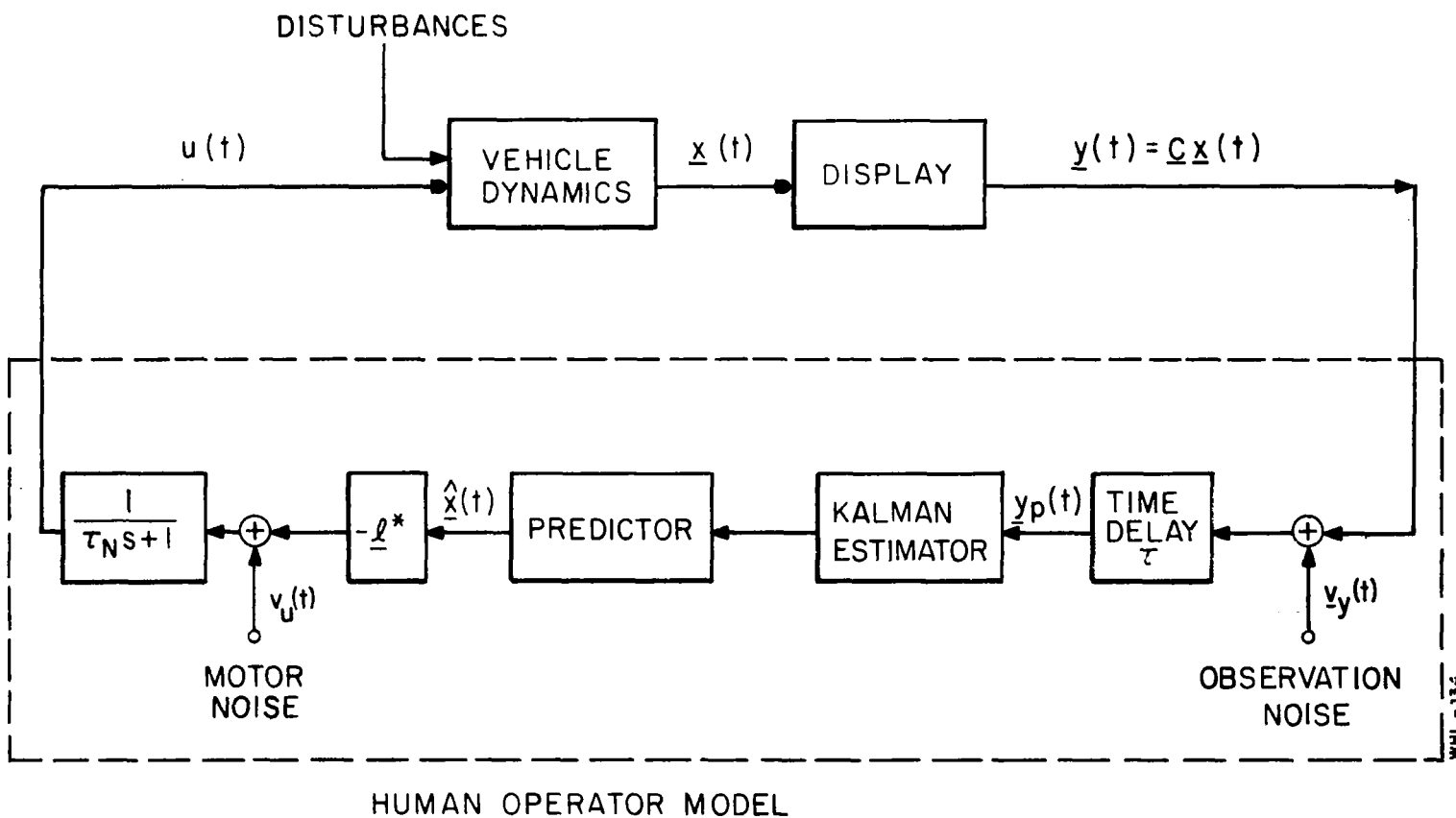


FIG. 1 THE OPTIMAL-CONTROL MODEL FOR PILOT-VEHICLE SYSTEMS

The "adjustable" portion of the pilot's response strategy consists of: (a) a Kalman filter to provide the human with the best estimate of the system states; (b) an optimal predictor to compensate partially for the human's inherent time delay; and (c) an optimal control law, designated as $-k^*$ in Figure 1, which operates on the estimated state vector. These elements are presumed to be structured by the human so as to minimize the cost functional within the limits imposed by his inherent limitations.

2.2.2 An Observation Noise Model for Controller Remnant

Our model for controller remnant is reviewed in detail in References 6-8. We originally developed a model for remnant based on multiplicative (i.e., proportional) sources of human randomness such as: (a) errors in observing the displayed variable, (b) errors in executing the intended control action, and (c) random fluctuations in controller gain and time delay. Most of these processes were found to be indistinguishable in their effects on controller remnant and were therefore combined into a single noise process — an equivalent observation noise.

Observation noise is most usefully represented as a *vector* process in which *each* sensory variable that is utilized by the controller is considered to be perturbed by a white noise process. These observation noise processes are assumed to be linearly independent of each other and of external disturbance signals. When the rms amplitudes of the quantities presented on the display are large compared to visual threshold effects, the power density levels of the noise processes vary proportionally with signal variance (Ref.8). In this situation, observation noise may be modelled as:

$$\underline{v}_y = P \cdot \underline{\sigma}_y^2 \quad (6)$$

where \underline{V}_y is a vector composed of the power density levels of the component noise processes; P is a normalized noise level, or "noise/signal ratio"; and $\underline{\sigma}_y^2$ is a vector composed of the variances of the quantities obtained from the display. This model for controller remnant has been verified by extensive analysis of single-axis manual control data.

The numerical value of the noise/signal ratio, P , has been found to be on the order of 0.01 units of normalized power per rad/sec (i.e., -20 dB) for a wide variety of single-loop control tasks. The relative invariance of this measurement suggests that a central-processing type of disturbance common to all tracking tasks is primarily responsible for remnant that is measured under nearly ideal viewing conditions. Random perturbations of human controller gain or time delay are possible manifestations of central-processing "noise" that would account for the remnant that is measured. We have generalized upon the notion of central-processing noise to develop the model for task interference which is summarized below.

2.2.3 A Model for Task Interference

Because the human can exert only a limited amount of physical or mental effort, his performance on a given psychomotor task generally degrades as he is required to perform more and more tasks simultaneously. Multiple tasks may thus be said to "interfere" with one another. Interference may occur in the visual system (because of scanning requirements), the motor system (if intermittent control becomes necessary), and the central-processing system (because of "sharing of attention").

A model for central sources of interference has been developed and is described in References 9 and 10. Development of this model

parallels the development of the model for controller remnant in that the various sources of interference are reflected to an equivalent perceptual source of interference. For mathematical convenience, we treat interference as occurring among the perceptual subtasks that are embodied in the entire task environment.

The model for interference is based on the primary assumption that the controller has a fixed amount of "capacity" or "attention" which must be shared among the various tasks to be performed. The effects of capacity-sharing are modelled by the following equation:

$$P_m^{(M)} = \frac{P_o}{f_m} \quad (7)$$

where $P_m^{(M)}$ is the noise/signal ratio associated with the m^{th} perceptual task when a total of M tasks are performed simultaneously, P_o is the noise ratio that is measured when a single task is performed, and f_m is the fraction of capacity allocated to the m^{th} task. The noise/signal ratio is thus shown to vary inversely with the amount of "attention" devoted to a particular task. Since overall capacity or attention is presumed to be constant, the fractions of capacity must sum to unity. The noise/signal ratios associated with each of the subtasks must therefore obey the following rule:

$$\sum_{m=1}^M f_m = P_o \sum_{m=1}^M \frac{1}{P_m^{(M)}} = 1 \quad (8)$$

The human is assumed to distribute his attention, subject to the above constraint, to optimize some overall measure of performance.

This model for task interference has been validated in multi-variable continuous-control situations. The optimal control model described above has been used in conjunction with the model for interference to predict allocation of attention as well as tracking performance in these situations. In the following chapter of this report we show how the model for task interference may be applied to multiple-decision tasks and to tasks requiring decision plus continuous control.

3. ANALYSIS OF THE DECISION TASK

3.1 Introduction

We imposed three constraints on the selection of an experimental decision task. The first constraint was that the task be compatible with the existing theoretical structure for optimal control and estimation. Secondly, we desired a task for which the correctness or incorrectness of the subject's response be unambiguous. Finally, a certain amount of resemblance between the experimental task and a decision task encountered in flight situations was desired.

At the time we began this work, the state-variable model had been implemented only for task situations in which the inputs were continuous with time-stationary characteristics. Accordingly, we desired a task which required continuous observation and decision-making (albeit discrete response activity.) The amount of pre-experimental model development and implementation would thereby be minimized, and predictions of decision performance could be obtained via Kalman estimation techniques then currently implemented on our digital computer.

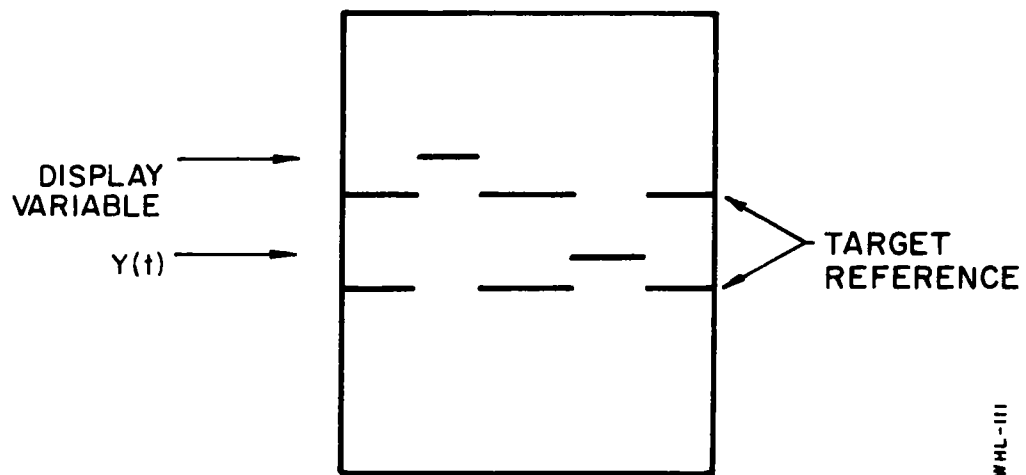
The requirement for unambiguous interpretation of the subject's response was not a trivial one. Ambiguity does exist, for example, in the case of a continuous signal-detection (i.e., "vigilance") task. Here the subject is required to detect a randomly-occurring signal in the presence of continuous noise. Since the duration of the signal is usually very brief — on the order of the subject's reaction time — the subject's response will occur after the signal has ceased. Hence, it is not always clear whether a given response corresponds to the occurrence of a signal

in the recent past or is, in fact, a "false alarm" (Ref.2). Partly for this reason, we decided against using a vigilance task.

Our choice of a decision task was influenced to some extent by an investigation, concurrently performed by NASA-Ames Research Center (Ref.11) and Bolt Beranek and Newman Inc. (Ref.12), of a pictorial runway display for making instrument approaches and touchdowns. This study included an experiment in which the pilots were required, in effect, to determine whether or not they were within the "landing window". In order to relate the work of this project to the concurrent study of approach and landing, we designed and used a decision task that was an idealization of the task of deciding whether or not the aircraft is in the landing window. This task is described below.

3.2 Description of the Task

The subject was presented with an oscilloscopic representation of a noisy glide-slope indicator along with two reference indicators showing the "target", or region of acceptable glide-slope error. The subject's task was to keep his response button depressed whenever he thought the true error was within the target area. In order to test our model for task interference, we provided two such decision tasks simultaneously to the subject. In the two-task situation, two noisy indicators were presented on the same display and the subject manipulated two response buttons. The two "error" signals were linearly independent and were in no way affected by the subject's response. The display format for the two-task situation is shown in Figure 2. (Additional details on the experimental decision task are given in Appendix A.)



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FIG. 2 DISPLAY FORMAT

The quantity displayed to the pilot was constructed as the summation of a "signal" plus a "noise" waveform. Thus,

$$y(t) = s(t) + n(t) \quad (9)$$

where $y(t)$ was displayed to the subject, $s(t)$ was a low-frequency random waveform that we defined as the "signal" (say, glide-slope error), and $n(t)$ was a random waveform of higher frequency that we defined as "instrument noise".

Both $s(t)$ and $n(t)$ were generated by Gaussian white noise processes which were shaped by filters of the following form:

$$F(s) = \frac{s}{s+0.05} \cdot \frac{1}{1 + \frac{s\sqrt{2}}{\omega_0} + \frac{s^2}{\omega_0^2}} \quad (10)$$

The element $s/(s+0.05)$ was included to guarantee that each signal had zero mean; the second-order Butterworth filter provided the primary shaping of the signal. The "bandwidth" of $s(t)$ was fixed at 0.5 rad/sec^{*}, and the input amplitude was adjusted so that $s(t)$ would be within the target area half the time during the course of an experimental trial. The bandwidth of $n(t)$ was sufficiently greater than that of $s(t)$ to enable the subject to distinguish between the noise and signal components of the displayed variable $[y(t)]$. Noise power and bandwidth were experimental variables. The white noise forcing functions driving the signal and noise filters were linearly uncorrelated.

* For semantic convenience, we refer to the critical filter frequency ω_0 as the "bandwidth" of the filter output.

Our mathematical description of this decision task consists, in part, of a state-variable representation of the dynamics of $s(t)$, $n(t)$, and $y(t)$. Let $\underline{x}(t)$ be a vector consisting of the state variables needed to describe the problem. Since two third-order filters were used to generate the signal displayed to the human, the state vector must contain six elements, two of which may be identified with $n(t)$ and $s(t)$. The equations of motion of $\underline{x}(t)$ are

$$\dot{\underline{x}}(t) = \underline{A} \underline{x}(t) + \underline{w}(t) \quad (11)$$

where \underline{A} is a matrix which accounts jointly for the dynamics of these random processes and $\underline{w}(t)$ is a vector of the (two) independent white driving noises.

The subject was not shown the full state vector. Instead, he was displayed the summation of two of the states. The display vector was thus a linear transformation of the state vector and may be written in general terms as

$$\underline{y}(t) = \underline{C} \underline{x}(t) \quad (12)$$

(Since the subject will usually obtain rate as well as displacement information from his display, we must consider the subject's perceptual input as a vector quantity even though only one quantity is displayed explicitly.)

The mathematical representation of the decision task is thus to a large extent identical to our mathematical representation of the continuous control task. (See Ref.4) Not surprisingly, then, we may directly apply a considerable portion of our optimal-control model to the analysis of the decision task. The major difference

is that we replace optimal control action with optimal decision behavior. Our model for the human's decision strategy is described below.

3.3 The Human's Optimal Decision Strategy

It is convenient to separate the human's decision strategy into two distinct operations: (a) estimating the underlying signal $s(t)$, given his perceptual information, and (b) generating his decision response given his best estimate of $s(t)$. The model for the human's estimation strategy is identical to that which we have applied in the continuous-control situation, as shown in Figure 3. The human's limitations are represented by an equivalent perceptual time delay and observation noise process, as before, and we retain the model elements of optimal prediction and Kalman filtering. The human is assumed to adopt an optimal decision rule which operates on his best estimate of the system states to yield a decision strategy which maximizes the expected utility of the decision. The optimal estimation and optimal decision aspects of the model are discussed separately below.

3.3.1 Optimal Estimation

The subject's ability to estimate the signal $s(t)$ is limited not only by the addition of simulated instrument noise, but also by the subject's own internal noise and time delays. The time delay (or "reaction time") arises from a combination of neural conduction times, central-processing delays, and limitations on neuromuscular bandwidth. To the extent that the human cannot compensate for this time delay by an optimal prediction strategy, time delay will be a source of performance degradation.

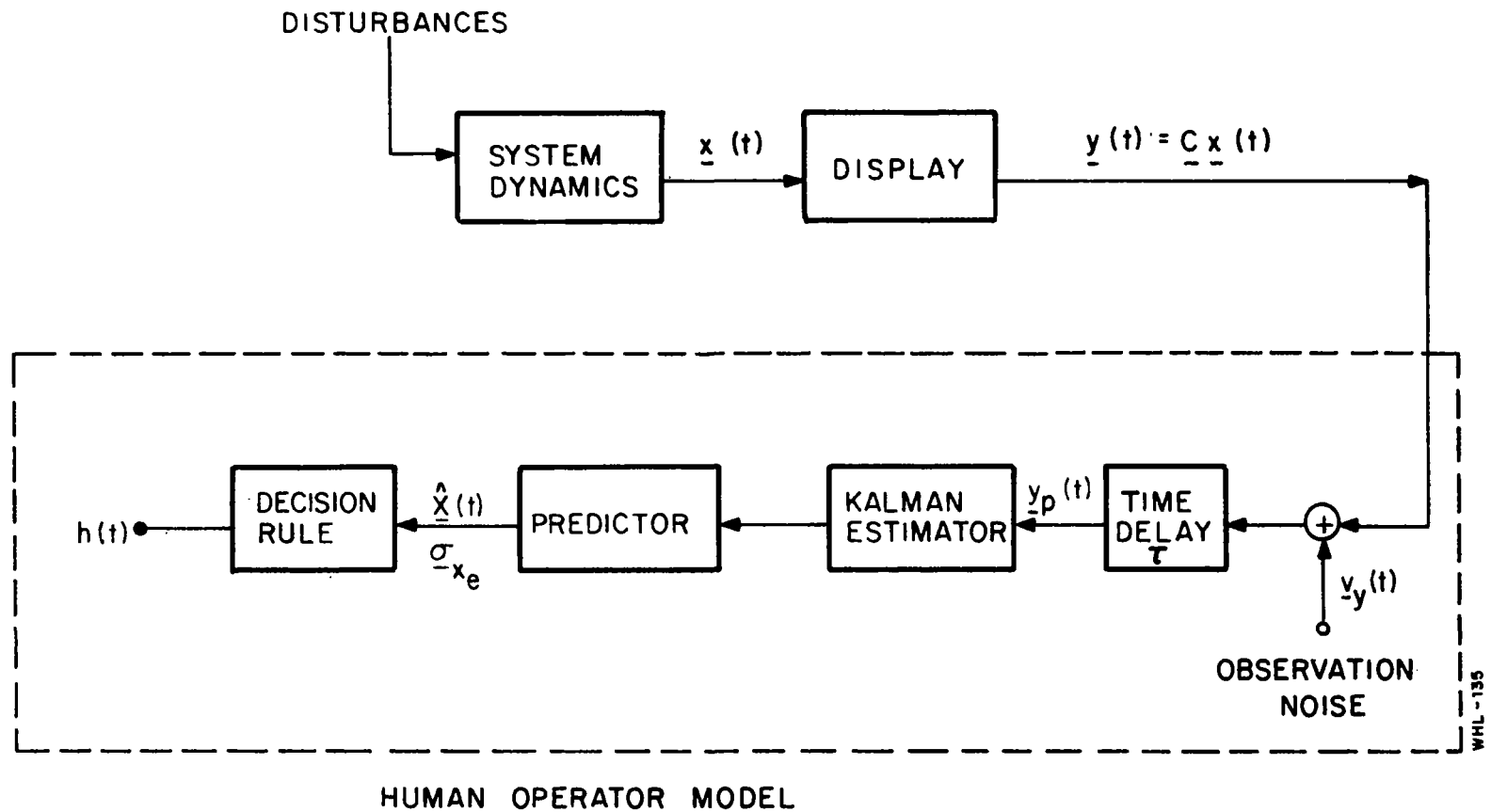


FIG. 3 MODEL FOR THE DECISION TASK

Second, and perhaps more important, is the randomness associated with human response behavior. That is, if we repeat the presentation of the entire waveform $y(t)$ on two different experimental trials, the subject will not depress and release his response button at exactly the same relative times from one trial to the next. With respect to this particular decision task, potential sources of human randomness include: (a) perceptual errors made in observing $y(t)$, (b) computational errors in estimating $s(t)$ based on the perceptual input, and (c) variations in the human's effective time delay. For mathematical convenience, we combine all sources of randomness into an equivalent perceptual, or observation, noise process. This treatment of decision randomness is parallel to our treatment of human controller remnant (see Refs.6-8).

The human's perceptual input is thus considered as a noisy, delayed version of the quantity presented on the display and is represented as

$$\underline{y}_p(t) = \underline{y}(t-\tau) + \underline{v}_y(t-\tau) \quad (13)$$

where $\underline{y}_p(t)$ is the vector of perceived quantities, τ is the human's effective time delay, and $\underline{v}_y(t-\tau)$ is a vector of equivalent observation noise process. (For the task considered here, the vector \underline{v}_y contains two components, v_y and \dot{v}_y , to represent observation noise processes associated with estimation of displacement and velocity, respectively.) In keeping with our previous treatment of human observation noise, we consider $\underline{v}_y(t)$ to be composed of white gaussian noise processes that are linearly independent of each other and of system forcing functions.

Since the displayed quantity is generated by linearly filtered white noise, the signal $\underline{y}(t)$ is, by definition, a sample function of a gauss-markov process (Ref.13). This type of random process has the following properties which justify our assumptions of optimal estimation and prediction:

1. The current "state" of the process contains all the useful information about the process. Thus, for most practical purposes, the entire past history of $\underline{y}(t)$ is "summarized" by the current value of the state vector, $\underline{x}(t)$.
2. The best estimate of the state vector is given by a Kalman filter cascaded with an optimal predictor which operates on the noisy input variable $\underline{y}_p(t)$ (Ref.13). This filter is linear and time-invariant, and the difference between the instantaneous value of the state vector and the best estimate is also time invariant. (This difference, or "estimation error", has a variance which we denote by σ_e^2 .) The estimate of the state vector, denoted by $\hat{\underline{x}}(t)$, is "best" in the sense that it is the minimum-variance as well as the maximum-likelihood estimate. (Ref.14)
3. The pair $(\hat{\underline{x}}(t), \sigma_e)$ constitutes a sufficient statistic to test hypotheses about $\underline{x}(t)$ based on the noisy data $\underline{y}_p(t)$. This is so because all the relevant information that can be extracted from $\underline{y}_p(t)$ is contained jointly in $\hat{\underline{x}}(t)$ and σ_e (Ref.14).

Note that the Kalman filter may be used to predict the variance of the estimation error as well as the instantaneous best estimate of the state vector. (Predictions of the instantaneous estimation error cannot be obtained; otherwise, the state vector could be estimated perfectly.) In the following section we show

that knowledge of the rms estimation error is needed to generate the correct decision strategy.

3.3.2 Optimal Decision Rule

The general expression for the optimal decision rule has been derived in Chapter 2 as

$$H(t) = \begin{cases} H_1, & \text{if } \frac{P(h_1|z)}{P(h_0|z)} > \frac{U_0}{U_1} \\ H_0 & \text{otherwise} \end{cases} \quad (14)$$

where $H(t)$ is the subject's instantaneous decision response, $h(t)$ is the state of the world, $z(t)$ represents the data upon which the human bases his decision, and U_0 and U_1 relate to the utilities of the various correct and incorrect decision possibilities. Let us identify h_1 as the condition for which the signal $s(t)$ is within the target boundaries (denoted by $+Y_T$). The condition h_0 represents an outside-the-target condition. Similarly, H_1 and H_0 represent the human's decision that the signal is either inside or outside the target area. For the problem considered here, the data denoted by the general expression $z(t)$ consist of the instantaneous best estimate $\hat{x}(t)$ and the rms estimation error σ_e . Although the Kalman filter yields the full \hat{x} and σ_e vectors, only those elements corresponding to the signal $s(t)$ are needed for making the decision.

We now reformulate the general decision rule of Equation (14) in terms of problem variables:

$$H(t) = \begin{cases} H_1 & \text{if } \frac{P(|s(t)| \leq Y_T | \hat{s}(t), \sigma_{s_e})}{P(|s(t)| > Y_T | \hat{s}(t), \sigma_{s_e})} > \frac{U_0}{U_1} \\ H_0 & \text{otherwise} \end{cases} \quad (15)$$

For any U_0/U_1 , we may find a "decision boundary" Y_D such that

$$\frac{P(|s(t)| \leq Y_D | \hat{s}(t), \sigma_{s_e})}{P(|s(t)| > Y_D | \hat{s}(t), \sigma_{s_e})} = \frac{P(|s(t)| \leq Y_T | \hat{s}(t), \sigma_{s_e})}{P(|s(t)| > Y_T | \hat{s}(t), \sigma_{s_e})} \cdot \frac{U_1}{U_0} \quad (16)$$

Thus, whatever the utility matrix, the subject's optimal decision strategy is to respond "in" whenever his best estimate of $s(t)$ is less than some predetermined decision boundary.

The relation of the decision boundary to the actual target boundary depends on the ratio U_1/U_0 . For example, if the penalty for incorrectly deciding that $s(t)$ is on target is much greater than the penalties and rewards associated with the remaining decision possibilities (as might be the case in making a landing decision), the subject should set his decision boundaries to span a narrower range than the actual target boundaries. This strategy will cause him to make fewer errors of the expensive type at the cost of making more errors of the less costly type. If U_1 and U_0 are equal (as presumably was the case in our experiments), the subject should adopt the actual target boundary as his decision boundary.

3.4 Predicted Decision Performance

In this section we show how the model described above may be used to predict the subject's decision error. Only the principal theoretical results are presented here; for more details on the computational procedure, see Section B.2 of the Appendix. Single-task and two-task situations are discussed separately.

3.4.1 Single-Task Decision Performance

We analyze here the single-task decision situations that were explored experimentally. The principal performance measure is the "decision error", defined as the probability that the subject will make either type of decision error at any instant of time.* That is,

$$\text{Decision Error} = P(H_1, h_0) + P(H_0, h_1) \quad (17)$$

The subject is assumed to be penalized equally for either type of decision error. No reward is given for a correct decision. We shall, therefore, treat the decision error as a "cost" that is to be minimized (rather than a "utility", of negative numerical value, that is to be maximized).

We consider two experimental variables: the critical frequency ("bandwidth") of the filter used to generate the simulated instrument noise, and the ratio of "signal" power to "noise" power. In addition, we must select values for the human's time delay and observation noise levels. Let us fix the time delay at 0.2 sec.-- a value that is typical of the effective delays inferred from

* We interpret this probability as a prediction of the fraction of time that the subject's decision response will be in error over the course of an experimental trial.

studies of manual control behavior. Let us also assume that the observation noise levels are proportional to signal variance, and that the constant of proportionality P is the same for displacement and rate perception.* This treatment is consistent with our treatment of controller remnant.

Rather than specify a single, nominal value for the human's internal noise/signal ratio, we shall treat this model parameter as an analytical variable. We have two reasons for doing this. First, we intend to account for the effects of task interference through changes in noise/signal ratio. Accordingly, we must investigate the relation between predicted decision error and noise/signal ratio. Second, we require experimental evidence to ascertain the value of noise/signal ratio that corresponds to single-task performance (which, as we shall see, varies from subject-to-subject).

Predicted decision error is shown as a function of noise/signal ratio in Figure 4. Curves are shown for each of the single-task conditions that were investigated experimentally. The filter bandwidth for the noise process $n(t)$ and the ratio of signal power to noise power is given for each of the conditions in the legend accompanying the figure.

For the most part, the curves shown in Figure 4 behave as one would expect. Predicted decision error increases as the simulated instrument noise power increases and as the human's internal noise increases. There is one unexpected result, however. The rank order of the two tasks corresponding to a σ_s^2/σ_n^2 of 22 (Tasks B and C) depends on the noise/signal ratio parameter associated with the

* A modification has to be made to the model of Equation (4) to account for the fact that the subject's display contains two reference levels (the two target boundaries) instead of the single zero reference that is usually presented. This modification is described in Section B.1 of the Appendix.

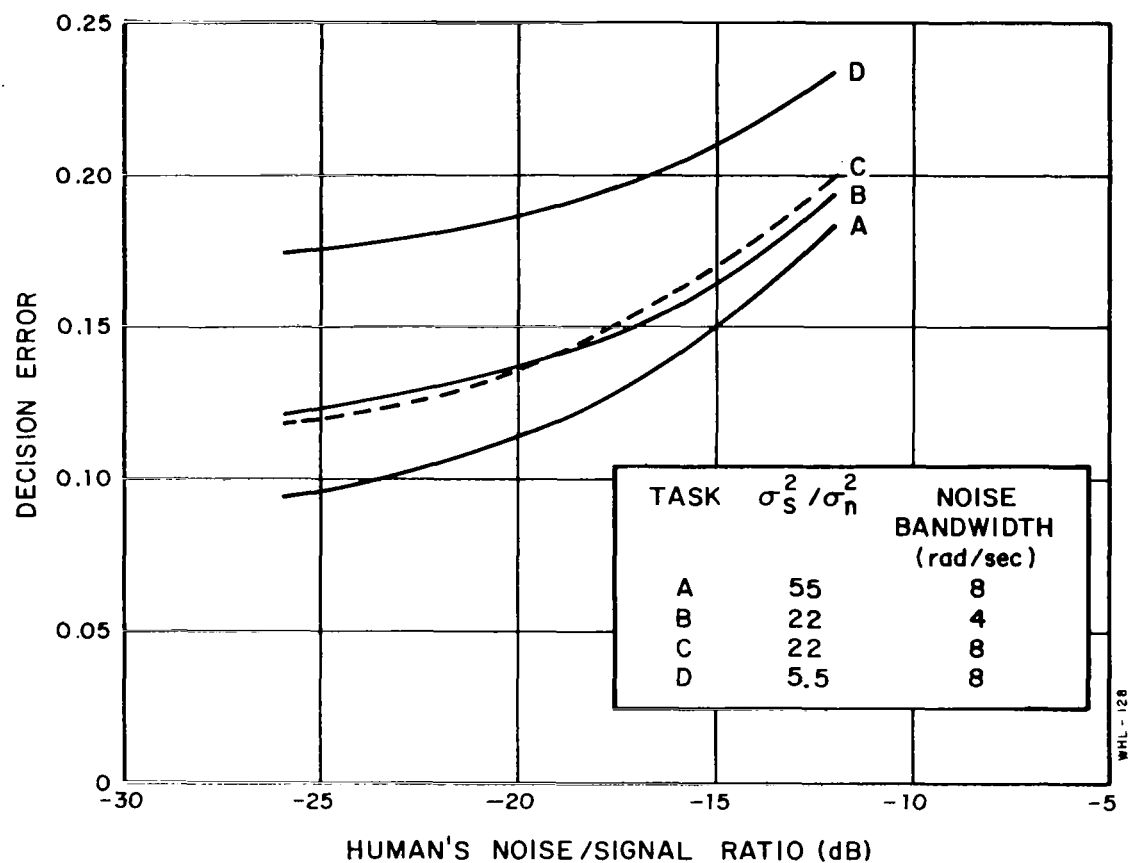


FIG. 4 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED DECISION ERROR
Signal Bandwidth = 0.5 rad/sec

human. These two tasks differ with regard to the bandwidth associated with the noise process (4 rad/sec for Task B, 8 rad/sec for Task C). For low levels of noise/signal, a lower score is associated with Task C. We would expect this to be the case, since the greater separation between signal and noise bandwidths for this task should allow the subject to distinguish signal from noise more accurately. The higher noise bandwidth associated with Task C, however, becomes a liability when the human's noise/signal ratio is relatively large, because the observation noise level associated with velocity perception is proportional to the variance of indicator velocity. Thus, for high noise/signal levels, velocity perception degrades more for Task C than for Task B, with the result that Task C now becomes the more difficult of the two. For a noise/signal ratio of -20 dB, predicted decision scores are essentially identical for Tasks B and C.

The numerical value chosen for the human's time delay does not appear to affect the relationships among the four curves shown in Figure 4. The relation between decision error and noise/signal ratio is shown for three time delays in Figure 5 for the easiest and most difficult of the four decision tasks. As expected, an increase in time delay will yield a higher decision error for a given level of human noise/signal. The shape of the error-vs-noise/signal curve does not depend on time delay, however, and the effects of task parameters on decision error are unaffected by time delay. Thus, the same *increment* in decision error is predicted for a particular change in task parameters or for a change in noise/signal ratio from one specific level to the next when the time delay lies within the range of 0.1 to 0.3 second.

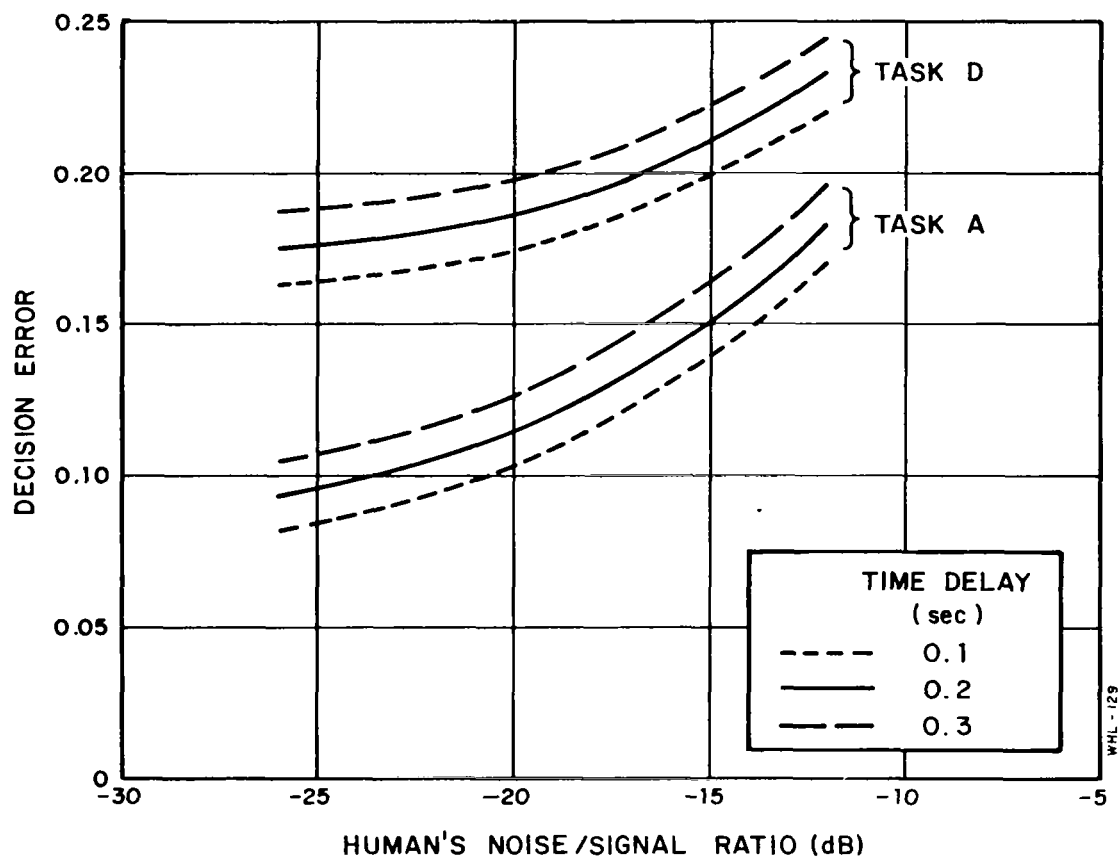


FIG. 5 EFFECT OF TIME DELAY AND NOISE/SIGNAL RATIO ON PREDICTED DECISION ERROR SCORE

The converse is not true, however, when one attempts to infer an increment in observation noise level from a pair of decision error scores. For example, the pair of scores 0.10 and 0.15 represents about a 9 dB increment in noise ratio for Task A when a time delay of 0.2 second is assumed, but only a 6.5 dB increment when a 0.1 second delay is considered. If we intend to infer noise/signal ratios from experimental decision scores, then our interpretations could be appreciably in error if the subject's true delay were markedly different from the 0.2 second that we have assumed. We have, however, found average time delay to lie within a relatively narrow range about this value for the various manual control experiments that we have conducted. Accordingly, we do not expect to introduce appreciable modelling error by assuming an effective time delay of 0.2 second for the decision tasks.

The foregoing analysis has been conducted on the assumption that the subject will select a decision boundary equal to the target boundary; that is, he will hold the response button down whenever he estimates the "signal" to be within the target. This would appear to be the optimal decision strategy for the situations we have investigated; namely, where the a priori probability of the signal being on target is 0.5 and the costs of either type of decision error are equal. It is nevertheless possible that the subject will adopt a utility matrix that differs somewhat from that assigned by the experimenter, in which case the decision boundary will not coincide with the target boundary. This is especially likely if the total decision error is relatively insensitive to the selection of a decision boundary. Accordingly, we have analyzed the easiest and most difficult of the experimental decision tasks to determine the relation between decision error and decision boundary.

Let DE_1 be the probability of a "false alarm"; i.e., the joint probability that the signal will be outside the target area and that the subject will respond otherwise. Conversely, let DE_0 be the probability of a "miss"; i.e., the fraction of time that the subject fails to respond properly when the signal is on target. The total decision error is defined as the probability of either type of decision error and is simply $DE_0 + DE_1$. For the situation in which equal costs are assigned to the two types of decision error, the overall performance measure is identical to the total decision error.

In Figure 6 we show the effects of the decision boundary on the component and total decision error scores for Tasks A and D. The independent variable shown on the abscissa is the decision boundary Y_D , normalized with respect to the target boundary Y_T . The decision area is assumed to be symmetric about zero: i.e., the subject indicates a "hit" whenever he estimates the signal to be within the limits of $-Y_D$ and $+Y_D$.

For Task D we find that total error remains within 10 percent of the optimal error score for decision boundaries that range from 20 percent below to 20 percent above the target boundary. The component error scores, however, change markedly with a shift in the decision criterion. For $Y_D/Y_T = 0.8$, the predicted miss rate is about twice the false alarm rate. Conversely, for $Y_D/Y_T = 1.2$, the false alarm rate is about three times the miss rate. Decision performance for Task A is somewhat more sensitive to decision criterion in that a ten percent deviation in the decision boundary has the same effect on total error score. The relative magnitudes of the component scores show the same trend as is observed for Task D. In summary, we see that the subject may effect a considerable trade-off between false-alarm and miss rates without

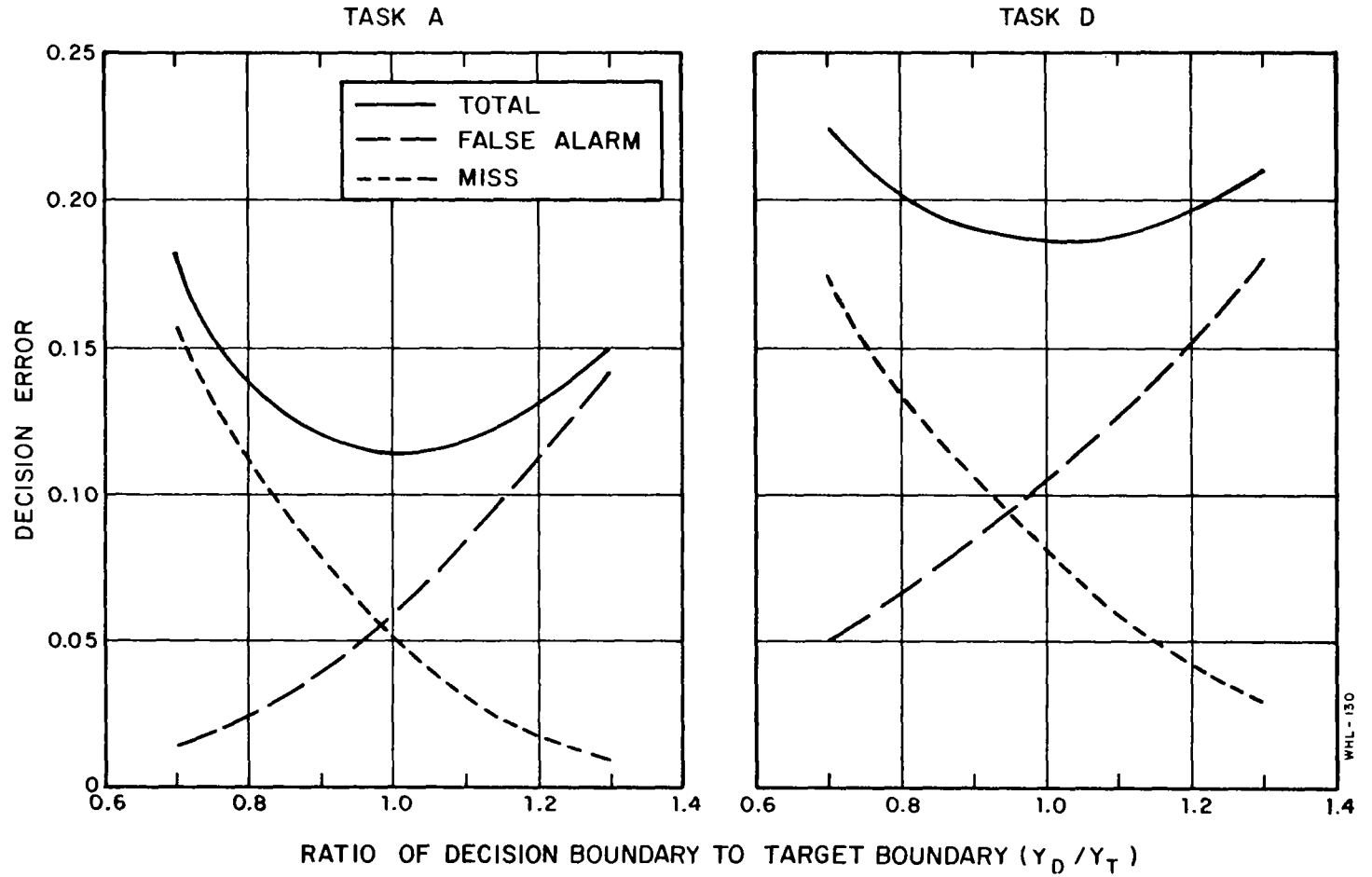


FIG. 6 EFFECT OF DECISION BOUNDARY ON PREDICTED COMPONENT AND TOTAL DECISION ERROR SCORES

seriously affecting his total score. In this sense, overall decision performance is relatively insensitive to decision criterion.

3.4.2 Multiple-Task Performance

It has been amply demonstrated that the human's performance on a given task generally degrades when a multiplicity of tasks are performed concurrently. We have shown this to be true for certain manual control situations, and we have developed and validated a model to account for the effects of task interference in multi-variable continuous-control situations (Refs.9 and 10). This model may be applied in a straightforward manner to predict performance on multiple-decision tasks.

Task interference is assumed to manifest itself as an increase in the human's internal noise/signal ratio according to the following relationship

$$P_i = P_o / f_i \quad (18)$$

where P_o is the noise/signal ratio that corresponds to single-task performance, P_i is the ratio associated with the i^{th} subtask in a multi-task situation, and f_i is the fraction of attention devoted to that subtask. This relationship may be used in conjunction with the curves shown in Figure 4 to predict multi-task decision performance as follows.

Let us assume we first perform a calibration experiment in which we measure performance on a single decision task. The appropriate theoretical curve is used to determine the noise/signal ratio P_o that corresponds to this level of performance. If we know how much attention the subject will devote to the decision task in the multi-task situation, we increment the noise/signal

ratio by the amount indicated in Equation (18) and refer again to the appropriate theoretical curve to predict the multi-task score. If we do not know a priori how the subject will allocate his attention, we obtain curves of performance versus attention for each component task and use these to determine the allocation of attention which minimizes some measure of total-task performance.

To illustrate this procedure, let us analyze the situation in which the subject is required to perform Tasks A and D simultaneously. The performance index to be minimized is the combined decision error, which is defined as the summation of the total decision error scores for the two component tasks. We assume that the subject has a relatively fixed information-processing capacity which he applies fully to his decision task, however complex or simple that task may be. In other words, his fractions of attention must sum to unity over the component tasks. Thus, if the subject devotes the fraction f_A to Task A in the two-task situation, he will devote the fraction $f_D = 1 - f_A$ to Task D. The noise/signal ratios associated with the two tasks will be:

$$\begin{aligned} P_A &= P_O / f_A \\ P_D &= P_O / (1 - f_A) \end{aligned} \tag{19}$$

Using these relationships, along with the theoretical curves relating decision score to noise/signal ratio, we can compute component and total decision scores as a function of attentional allocation. The predicted (optimal) division of attention is the one which corresponds to the minimum total performance score.

Predicted component and total decision error scores are shown in Figure 7 as a function of the fraction of attention devoted to Task A. (A noise/signal ratio of -20 dB is associated with full attention.) We note that the component decision error scores are relatively insensitive to lack of attention and that an increase in one of the component scores is, to some extent, compensated for by a decrease in the other component score as the allocation of attention changes. Consequently, the combined decision error score is extremely insensitive to the subject's division of attention. This score remains within 10 percent of its minimum value as the subject's attention ranges from 80 percent on Task A to 80 percent on Task D. Previous analysis of multi-axis tracking tasks with stable dynamics has also indicated a relative insensitivity of total-task performance to division of attention. (See References 9 and 10.)

Because of the insensitivity of total-task performance to attention, we cannot expect to validate our method for predicting division of attention using decision tasks of the type we have been investigating. We can, however, test the accuracy of the model to predict the effects of interference on the total performance score. For example, in the absence of interference, the combined scores for Tasks A and D would be about 10 percent less than the optimal score predicted in Figure 7. Since performance on Task A is the most sensitive to noise/signal ratio of all the decision tasks considered in this study, a larger fractional increase in total score would be expected if two tasks of type A were performed simultaneously. The subject would presumably devote 50 percent of his attention to each component task on the average, and the decision error score for either task would increase by about 17 percent. This latter situation has been investigated experimentally, and in Section 4.2 of this report we show that theoretical and experimental results are in good agreement.

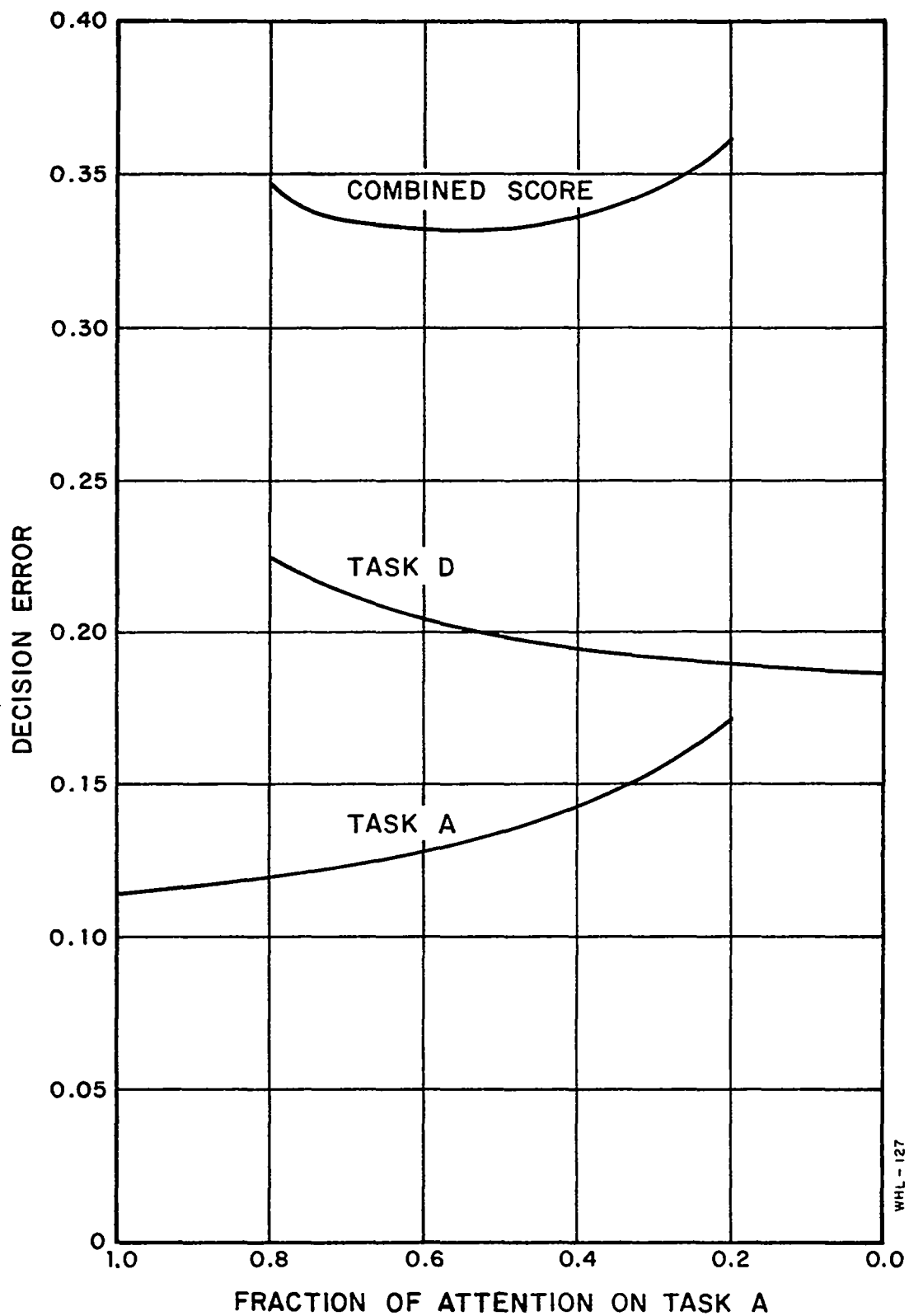


FIG. 7 EFFECT OF ATTENTION ON PREDICTED DECISION ERROR SCORES

The analysis procedure described above may also be employed to predict human performance when a decision task is performed concurrently with a continuous control task. In this case, the theoretical relation between some measure of tracking performance (say, mean-squared error) and the human's noise/signal ratio is used, along with the corresponding curve for decision performance. We again find the division of attention that corresponds to minimum total score, where the "total score" might be specified as a weighted sum of decision error plus mean-squared tracking error.

Since continuous tracking tasks differ from decision tasks in many respects, it is not obvious that the same noise/signal ratio P_0 should be associated with "full attention" for both tasks. We have seen that the ratio corresponding to single-task performance may depend on the sensitivity of performance score to noise/signal ratio (Ref.9). In general, this sensitivity is greater for most laboratory tracking tasks than for the decision tasks considered here. Furthermore, we would expect the subject's noise/signal ratio to depend on how well the subject had learned the task. This is especially true for the decision task, where the noise/signal ratio must be inferred from the decision error score.

Accordingly, we shall add an additional degree of freedom to the model for task interference when the tasks are qualitatively different from one another. For the situation in which concurrent performance of a single decision and a single tracking task is to be analyzed, the model of Equation (19) is revised as follows:

$$\begin{aligned} P_T &= P_{0T} / f_T \\ P_D &= P_{0D} / (1 - f_T) \end{aligned} \tag{20}$$

where the subscripts T and D refer to tracking and decision performance, respectively. Experimental results on combined tracking and decision performance are presented in Section 4.3.

3.5 Model-Validation Procedures

The model for the optimal decision-maker described above can be used to predict the fine structure of the human's decision strategy as well as to predict overall decision performance. For example, one can obtain a predicted describing function which represents the subject's optimal estimation strategy: i.e., the linear transfer between the displayed variable $y(t)$ and the best estimate of the signal, $\hat{s}(t)$. In addition, one can investigate the "remnant" portion of the decision strategy, which is simply the spectrum of the estimation error $s_e(t)$.

Precise measures of these frequency-domain descriptors cannot be extracted from the experimental data, however. Unlike the task of continuous control, the decision task does not require the subject to respond in a manner that is linearly related to $\hat{s}(t)$. Thus, we can test the model only with respect to its ability to predict decision error scores.

A variety of experimental conditions is required to test the predictive accuracy of the model. This is so because the model contains two "free" parameters relating to human limitations (effective time delay and noise/signal ratio). Either of these parameters could be adjusted to match the subject's decision performance under any given condition. Thus, we must explore the model's ability to predict *differences* in decision performance that arise from variations in the parameters of the task. Ideally, we would hope to find that performance differences of this type

could be accounted for with fixed values for time delay and for single-task noise/signal ratio.

The same model-validation technique applies to the tracking task in the combined tracking and decision task. That is, we determine the extent to which tracking performance alone and tracking performance in the two-task situation can be matched by a consistent set of model parameters.*

* Because the hardware was not available for linking to BBN's digital computer, we were not able to analyze pilot describing functions and remnant spectra as we have usually done in the past. Consequently, model-matching was performed by selecting noise/signal ratios and subjective cost functionals to match the available performance scores (mean-squared tracking error, error rate, and control displacement). Time delay was held fixed at 0.17 second and motor noise at about -25 dB--values that have been found to be typical of K/s tracking. We do not feel that the validity of our analysis has suffered appreciably from the lack of frequency-domain measures. We have analyzed K/s tracking performance many times in the past, and we have found that model parameters which closely match the performance scores will usually reproduce accurately the describing functions and remnant spectra. (See References 4-10.)

4. THE EXPERIMENTAL PROGRAM

An experimental program was undertaken to test the validity of the model for decision-making presented in the preceding chapter and to provide additional tests of our model for task interference. The following situations were explored: (a) single decision tasks, (b) multiple decision tasks, and (c) simultaneous control and decision-making. The principal results of these experiments are presented in this chapter.

Because of certain methodological problems associated with the particular decision task used in this study, not all of the experimental results provided a conclusive test of the model. This was particularly true for the experiment on simultaneous decision and tracking. These and other factors relating to discrepancies between theory and experiment are explored in some detail in the discussion of results given in Chapter 5.

4.1 Effect of Task Parameters on Decision Error

An experiment was conducted to determine the effect of changes in task parameters on decision error and on inferred noise/signal ratio. Our primary objective was to test the predictive capability of our model. Specifically, we wished to determine the extent to which decision performance could be predicted by a model with fixed values for the human's time delay and noise/signal ratio.

4.1.1 Experimental Procedures

Four subjects were provided with six training trials on each of the four decision tasks described in Section 3.2. Experimental conditions are summarized in Table 1. Following training, three "data" trials were conducted with the right-hand and left-hand

displays active. Subjects responded to only one signal during a given trial, with the remaining signal clamped at zero displacement. Additional details on subject training are given in Appendix A.

TABLE 1
EXPERIMENTAL CONDITIONS FOR SINGLE-TASK DECISION EXPERIMENT

Task	σ_s^2/σ_n^2	Bandwidth of $n(t)$ (rad/sec)
A	55	8
B	22	4
C	22	8
D	5.5	8

Bandwidth of $s(t) = 0.5$ rad/sec

The average decision error score served as the primary performance measure. The "decision error" was defined as the fraction of run time during which the subject was not indicating the true state of the signal $s(t)$. This score was computed as the sum of two component error scores: the "false alarm" rate (the fraction of time the subject decided that $s(t)$ was inside the target when it was actually out) and the "miss" rate (the reverse type of decision error).

The standard deviation of the total decision error score was estimated. This was defined as

$$\text{STD DEV} = \left[\frac{\sum_{i=1}^N (DE_i - \overline{DE})^2}{N(N-1)} \right]^{1/2} \quad (21)$$

where DE_i is the average score of the i^{th} subject for a particular task, \overline{DE} is the average score for all subjects on that task, and N is the number of subjects (in this case, 4). A mean noise/signal ratio was inferred for each task by reference to the appropriate theoretical curve (Figures C-1 to C-4, Appendix C). Standard deviations were estimated for the noise/signal ratio as follows. Ratios were found which corresponded to the mean decision error plus (and minus) one standard deviation; the absolute value of the difference between these noise ratios, divided by two, was taken as the approximate standard deviation.

4.1.2 Principal Results

Figure 8 shows the effects of task parameters on predicted and measured average decision performance. Standard deviations for the measured scores are also shown. Predictions were obtained with nominal values of 0.2 sec and -20 dB assigned to the time delay and noise/signal ratio parameters of the model.

For the most part, predicted and measured scores were in very good agreement. For Tasks A, B, and C, the measured decision error score varied by less than one standard deviation from the theoretical prediction. The decrease in "instrument noise" bandwidth from 8 to 4 rad/sec did not appreciably affect decision performance. (We had predicted that this would be the case if the human's noise/signal ratio were -20 dB.) The only notable discrepancy between theory and experiment occurred for the most difficult task (Task D); in this case, the measured score was

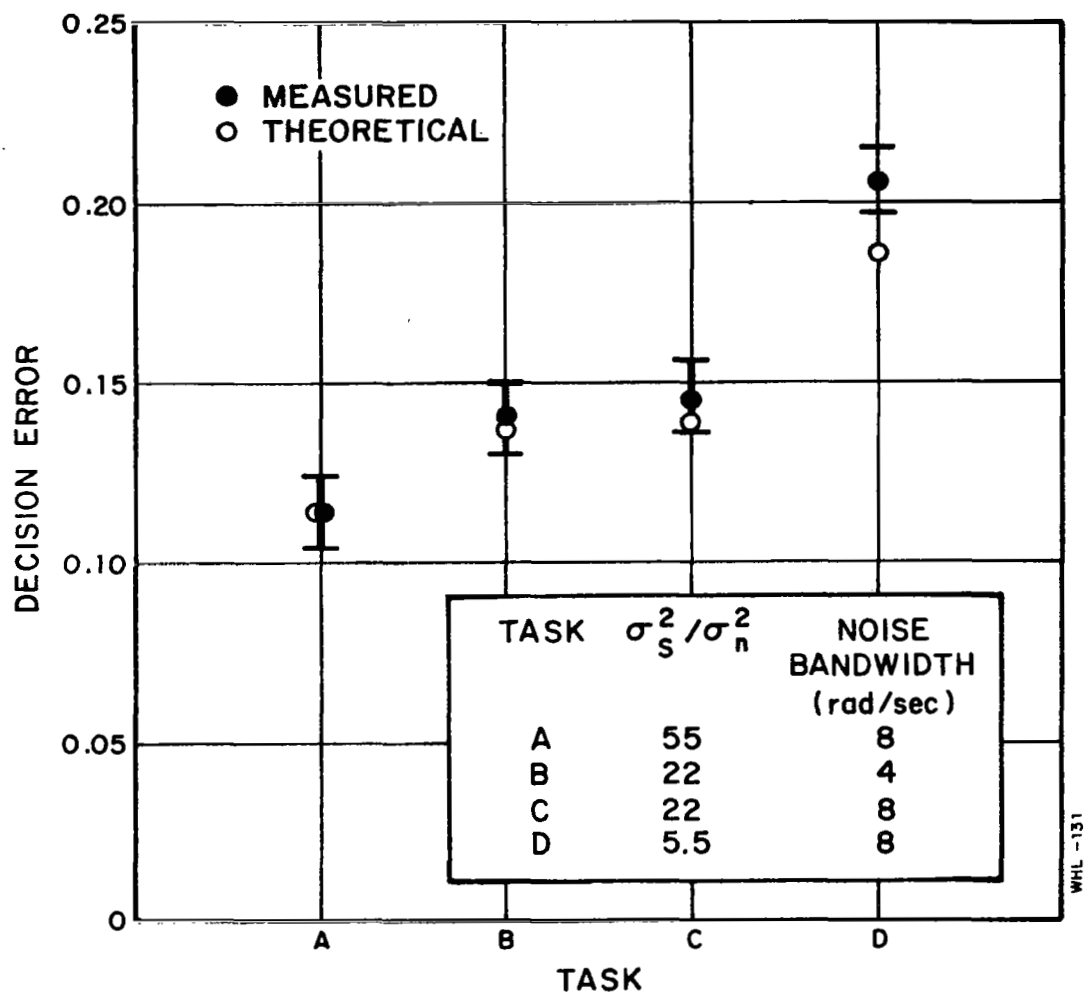


FIG. 8 EFFECT OF TASK PARAMETERS ON PREDICTED AND MEASURED DECISION ERROR

4 Subjects, 3 Trials/Subject

about 11 percent greater than the predicted decision error. A t-test performed on the subject means revealed that this difference, while small in absolute terms, was significant at the 0.05 criterion level.

Average scores for each subject are shown in Table 2. Also shown are the ratios of false alarm to miss rates, along with the noise/signal ratios inferred from the decision error scores. The false alarm rate was, on the average, about twice the miss rate for each of the four decision tasks. From Figure 6 we note that the false alarm rate should be about 50% greater than the miss rate for minimum total score. Furthermore, total score is shown to be relatively insensitive to a moderate trade-off between the false alarm rate and the miss rate. Thus, it would appear that the subjects adopted decision criteria that were appropriate to the tasks.

Decision error versus inferred noise/signal ratio is shown graphically for Tasks A, C, and D in Figure 9. Rectangular boxes about each datum point indicate ± 1 standard deviation of both the error score and the noise/signal ratio. (The results of Task B are not shown in this figure since they almost coincide with the results of Task C.) The theoretical curves of Figure 4 are superimposed on the experimental results.

Figure 9 shows that the noise/signal ratio increases almost linearly with decision performance, ranging from -20.0 dB for Task A to -15.6 dB for Task D. Since the ratios inferred for Tasks A, B, and C lie within one standard deviation of one another, we cannot ascribe any statistical significance to these differences. The noise/signal ratios associated with Tasks A and D, however, differ by about two standard deviations; this difference is too large to dismiss simply as experimental variability.

Overall, we conclude on the basis of this experiment that the model for decision-making described in this report has good predictive capability with respect to the class of decision tasks explored.

TABLE 2

EFFECT OF TASK PARAMETERS ON DECISION
ERROR AND INFERRED NOISE/SIGNAL RATIO

Subject	Task A	Task B	Task C	Task D
Decision Error				
DB	.142	.148	.172	.225
MH	.114	.123	.125	.212
WK	.108	.168	.151	.199
DM	.090	.126	.137	.193
Mean	.114	.141	.146	.207
Std. Dev.	.0108	.0105	.0101	.0071
Ratio: (False Alarm Rate)/(Miss Rate)				
DB	3.9	3.1	2.1	3.2
MH	1.7	1.5	1.8	1.3
WK	2.2	1.8	2.4	2.2
DM	1.6	1.6	2.2	1.9
Mean	2.2	1.9	2.1	2.0
Inferred Noise/Signal Ratio (dB)				
Mean	-20.0	-19.0	-18.6	-15.6
Std. Dev.	2.5	2.5	1.7	2.2

Average of 3 trials/subject.

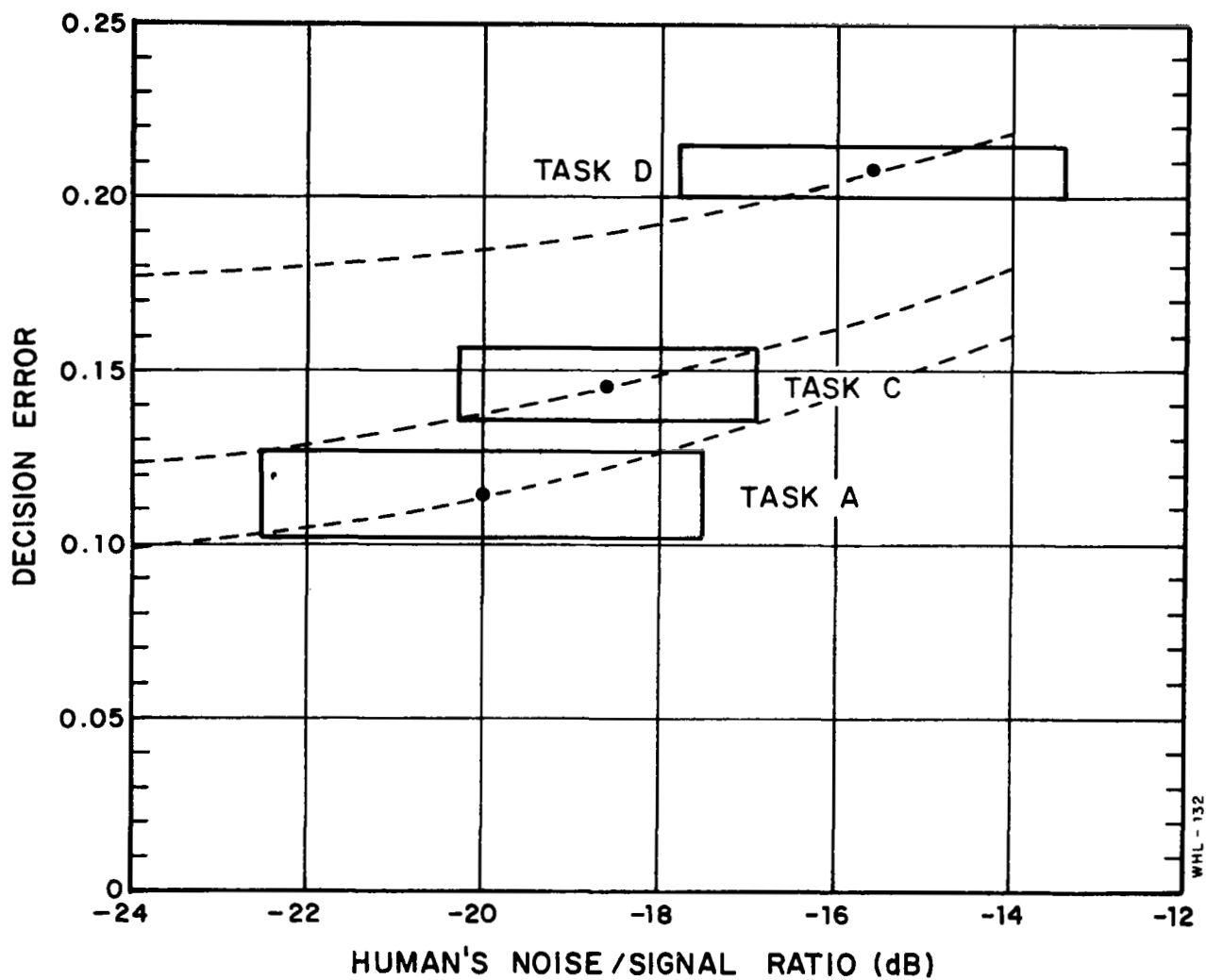


FIG. 9 DECISION ERROR SCORES AND INFERRED NOISE/SIGNAL RATIOS FOR THREE TASKS

4 Subjects, 3 Trials/Subject

Using fixed values for human time delay and noise/signal ratio, we have been able to predict decision scores to within 11 percent or better. At the same time, we note that wide range of noise/signal ratios is needed to match all decision scores perfectly. Factors which contribute to this latter result are discussed in Chapter 5.

4.2 Multiple Decision Tasks

This experiment was performed to validate our model for task interference in a decision-making context. Decision error scores were obtained for tasks performed singly and two at a time, and the difference between the 2-task and 1-task scores was tested against the difference predicted by the model.

4.2.1 Experimental Procedures

The subjects were provided with two decision tasks of the type identified as Task A in Table 1. The statistics of the left- and right-hand tasks were nominally identical, but the two display variables were linearly uncorrelated.* When two tasks were performed concurrently, the subjects were instructed to minimize the sum of the decision errors associated with each component task. The same four subjects who participated in the single-task experiment were used in this study.

After having been trained to an apparent asymptotic level of performance on the two-task situation, each subject performed four data sessions. Each session consisted of three trials:

* We originally had intended to vary the relative difficulty of the left- and right-hand tasks in an attempt to manipulate the subjects' division of attention. Pre-experimental model analysis revealed, however, that overall decision performance would be relatively insensitive to attention, even when the component decision tasks differed considerably. (See the analysis presented in Section 3.4.2.) Hence, we decided against using task difficulty as an experimental variable.

(a) a single task for the left hand, (b) a single task for the right hand, and (c) left- and right-hand tasks together.

4.2.2 Principal Results

Average decision error scores are shown in Table 3 for each subject for each task condition. Also shown are the scores averaged over the left and right tasks along with the average differences between 2-task and 1-task scores. Average decision error increased from 0.110 to 0.130 — an increase of about 18% — as the second task was added. A t-test showed this difference to be significant at the 0.001 level.

TABLE 3

EFFECT OF NUMBER OF TASKS ON DECISION ERROR
INFERRED NOISE/SIGNAL RATIO

Subject	Left Task		Right Task		Average Left and Right Tasks		
	1-Task	2-Task	1-Task	2-Task	1-Task	2-Task	Difference
Decision Error							
DB	.134	.160	.124	.137	.130	.148	.018
MH	.112	.131	.096	.114	.104	.122	.018
WK	.115	.138	.104	.123	.109	.131	.021
DM	.098	.117	.094	.118	.096	.118	.022
Average	.115	.136	.104	.123	.110	.130	.020
Std. Dev.	.0074	.0090	.0068	.0050	.0072	.0067	.0010

Average of 3 trials/subject

If our model for task interference is valid in this decision context, then the observed increment in decision score (averaged across the two tasks) should correspond to a doubling of the subjects' noise/signal ratio (again, averaged across the two tasks). In order to obtain a theoretical prediction for 2-task performance, we must refer to the theoretical curve of Figure C-1. From this curve we associate a noise/signal ratio of -20.8 dB with the average 1-task score of 0.110. Taking this point as a reference, we derive the curve shown in Figure 10 which relates the predicted increment in decision error to increments in noise/signal ratio (alternatively, to decrements in "attention"). The curve shown in the figure, then, is a segment of the theoretical curve of Figure C-1.

The increments in decision error and inferred noise/signal ratio that we obtained experimentally are shown in Figure 10 for comparison with the theoretical curve. The range of decision error and noise/signal ratio corresponding to ± 1 estimated standard deviation are also indicated. The increase of 0.020 in decision errors score that we measured corresponds to an increment of 3.3 dB in the inferred noise/signal ratio. This increase is within one standard deviation of the 3 dB increment predicted by our model for task interference. Similarly, the assumption of a 3 dB increment in noise/signal ratio leads to a predicted increase in error score of 0.018. A t-test of the average 2-task, 1-task difference scores shows that this prediction is not significantly different from the measured increase of 0.020. On the basis of this very good agreement between theory and experiment, we conclude tentatively that our model for task interference is applicable to the type of decision task explored in this study.

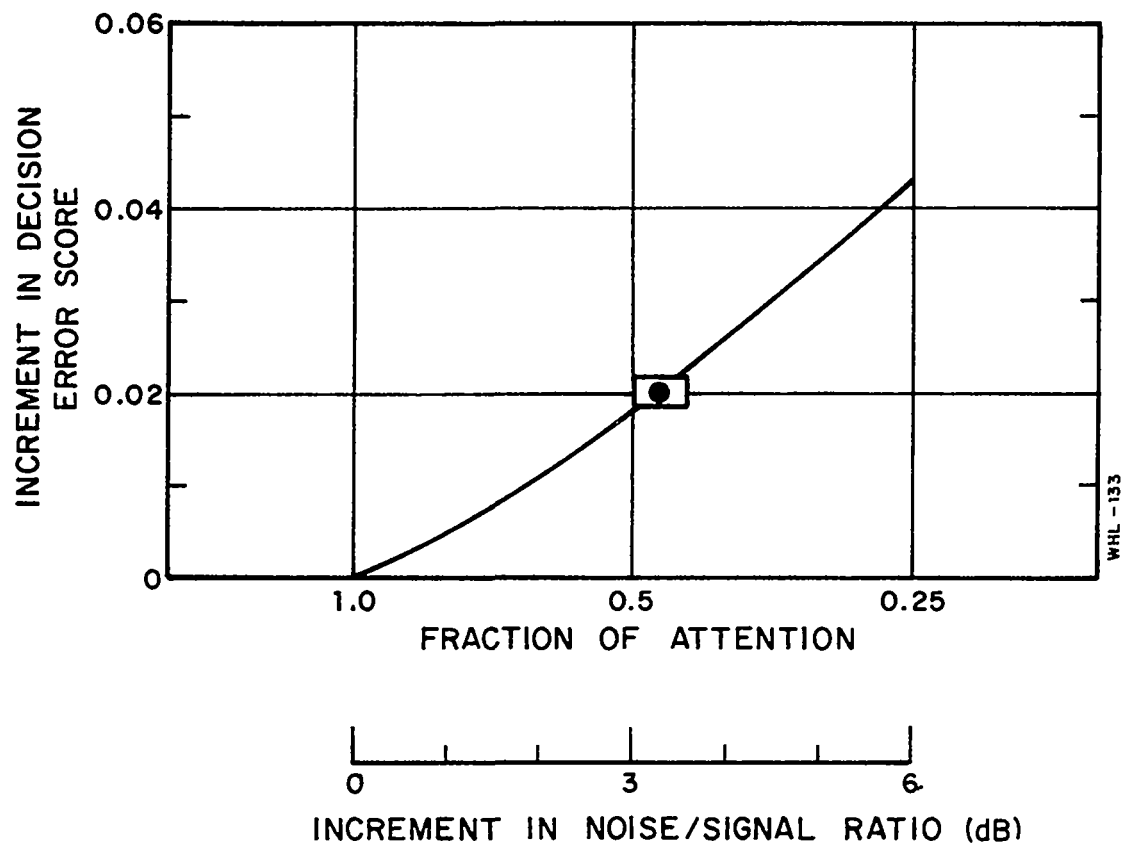


FIG. 10 EFFECT OF ATTENTION ON DECISION ERROR SCORE, TASK A
4 Subjects, 3 Trials/Subject

4.3 Simultaneous Control and Decision-Making

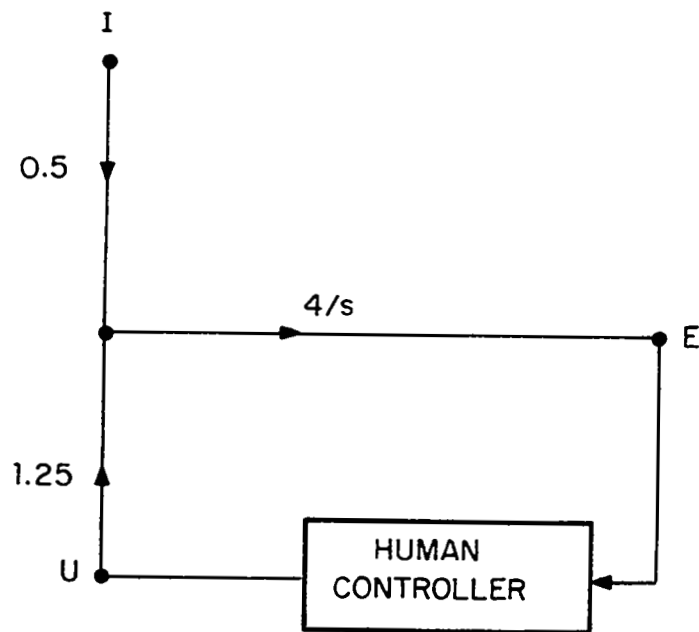
The experiment described above confirmed that the model for task interference, which had been validated previously in multi-variable control situations, could also be applied successfully to multi-task decision situations. The third and final experiment was conducted to determine whether this same model would account for interference between a decision task and a continuous control task performed concurrently.

4.3.1 Experimental Procedures

The subjects were presented with two tasks to be performed concurrently: a decision task (Task A, as described previously), and a continuous manual control task. The latter was a compensatory K/s tracking task of the type used in previous studies. The display format shown in Figure 2 was used, with the decision variable displayed on the left and tracking error displayed on the right. Display/response compatibility was maintained. The primary tracking performance measure was mean-squared tracking error; decision performance was measured in terms of decision error, as defined earlier in this chapter.

A diagram of the tracking task is given in Figure 11. All gains in this diagram are given in terms of units that correspond to settings of analog computer elements. Similarly, all mean-squared signal scores tabulated in this report are in terms of analog readings. Conversion factors are provided in Table 4 so that the reader may convert these scores to psychophysical units.

The input forcing function was constructed of 13 sinusoids to resemble a first-order noise spectrum with a critical frequency at 2 rad/sec. (See Appendix A of Reference 9 for additional



I = INPUT FORCING FUNCTION
 E = SYSTEM ERROR
 U = SUBJECT'S CONTROL SIGNAL

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FIG. 11 DIAGRAM OF THE EXPERIMENTAL TRACKING TASK

All gains given in analog-machine units
 Mean-squared input = .840 (analog units)²

TABLE 4

CONVERSION FACTORS FOR MEAN-SQUARED SIGNAL SCORES

Score	To Convert From Experimental Units, Multiply by	To Obtain
σ_e^2	1.2×10^3	(millirad visual arc) ²
$\sigma_{\dot{e}}^2$	1.2×10^3	(millirad/sec visual arc) ²
σ_u^2	4.7	newtons ²

details on the input.) In the absence of control activity, the input signal represented an rms velocity disturbance of approximately 3.7 degrees/second of visual arc. The control gain was such that 1 newton of force imparted a velocity of 4.6 arc-degrees per second to the error signal.

The subjects' instructions were to minimize decision error (DE) when performing the decision task alone, to minimize mean-squared tracking error (σ_e^2) when performing the tracking task alone, and to minimize a weighted sum of decision error and mean-squared tracking error when performing the two tasks concurrently. The overall performance measure for the two-task situation was defined as $J = \sigma_e^2 + 3 \cdot DE$. The subjects were not instructed as to how to apportion their total score among the component scores. Additional details on the training procedure may be found in Appendix A. Three of the subjects who had participated in the previous experiments were not available for this experiment and

were replaced by three new subjects. The newcomers were familiarized with the single-task decision situation, and all four subjects were trained to apparent asymptotic performance on the tracking task and on the combined decision-plus-tracking task. Data-taking consisted of at least three sessions of three trials each as described for the previous experiment.

4.3.2 Principal Results

Because subject-to-subject variability was quite high in this experiment, we have not averaged the performance scores across subjects. Instead, we examine the average performance of each subject separately.

Performance measures are shown for each subject's decision error, tracking error, and total performance score in Figure 12. One-task and two-task performance measures are compared. The 1-task total performance measure is defined as the sum of the mean-squared tracking error obtained when tracking was performed alone, plus three times the decision error that was obtained when the decision task was performed alone. This measure is the total score that we would predict for the 2-task situation if we were to assume no interference. Means and standard deviations for all performance measures (including mean-squared error rate and control force) are given in Table 5.

All of the 2-task, 1-task differences are in the expected direction. That is, each subject yielded higher performance scores in the 2-task situation than in the 1-task situation. This was true not only for the total performance measure but also for the component scores as well (including error-rate and control scores). The *magnitude* of these differences, however, varied quite a bit from subject-to-subject. The fractional increase in total performance score ranged from about 5% (subject WK) to about 45% (subject WR). The remaining two subjects (KC & HH) exhibited approximately a 15% increase in total score

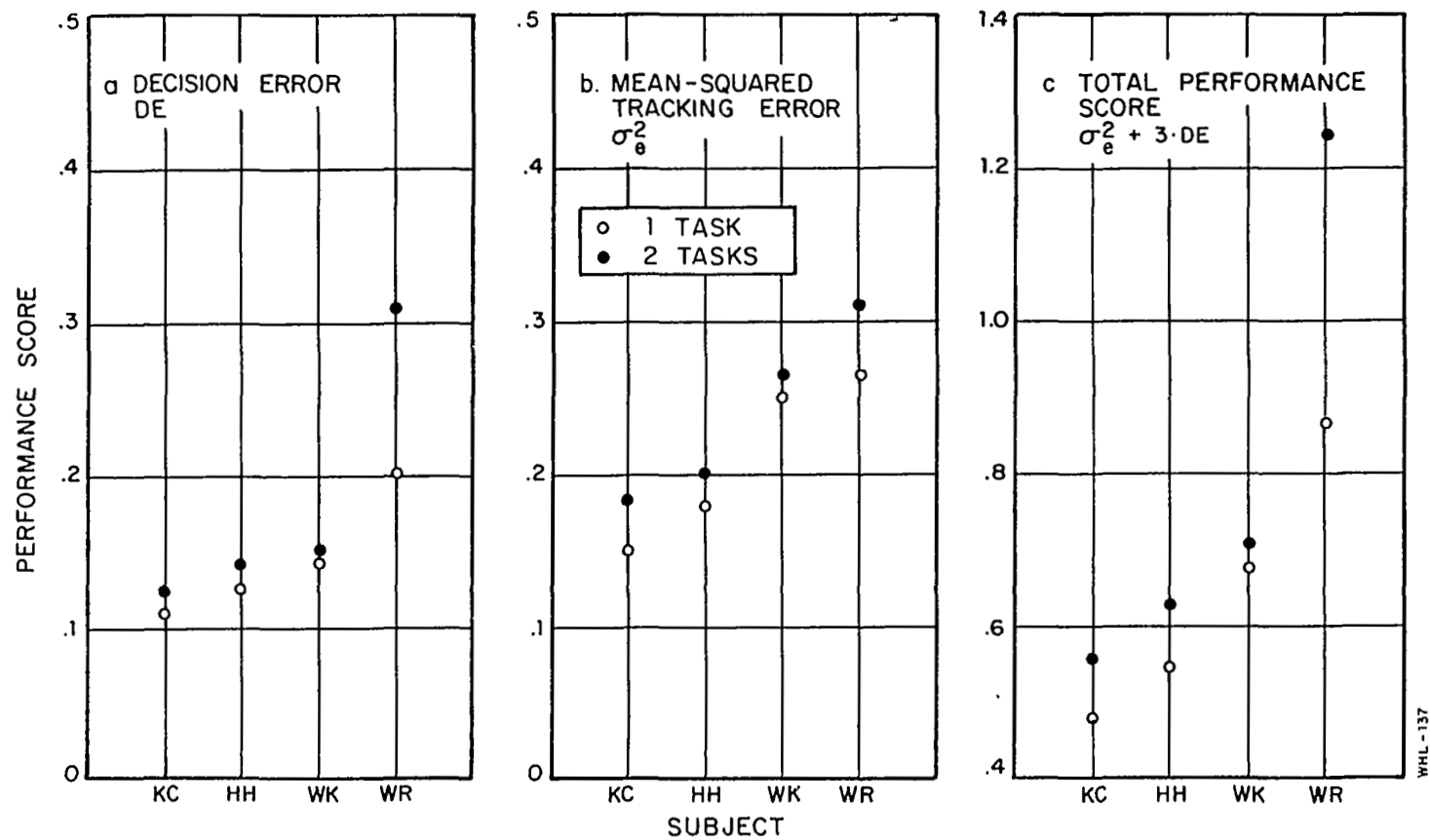


FIG. 12 PERFORMANCE MEASURES FOR SIMULTANEOUS DECISION AND CONTROL

Average of 4 Trials for Subjects KC, HH, WK
Average of 3 Trials for Subject WR

TABLE 5

AVERAGE PERFORMANCE SCORES FOR DECISION AND TRACKING

Scope	1-Task		2-Task	
	Mean	S.D.	Mean	S.D.
a) SUBJECT KC				
DE	.111	.003	.123	.008
3·DE	.333	.009	.369	.024
σ_e^2	.150	.006	.186	.003
σ_e^2	5.25	.192	6.14	.270
σ_u^2	.288	.010	.309	.011
$\sigma_e^2 + 3 \cdot DE$.483	.026	.555	.009
b) SUBJECT HH				
DE	.125	.004	.143	.007
3·DE	.375	.012	.429	.021
σ_e^2	.178	.006	.202	.005
σ_e^2	5.14	.336	6.60	.240
σ_u^2	.284	.014	.336	.087
$\sigma_e^2 + 3 \cdot DE$.553	.012	.631	.024

TABLE 5 (Cont.)

Scope	1-Task		2-Task	
	Mean	S.D.	Mean	S.D.
c) SUBJECT WK				
DE	.142	.002	.149	.003
3·DE	.426	.007	.447	.008
σ_e^2	.251	.006	.264	.011
σ_e^2	4.70	.180	6.48	.189
σ_u^2	.244	.009	.313	.021
$\sigma_e^2 + 3\cdot DE$.677	.010	.711	.012
d) SUBJECT WR				
DE	.200	.006	.311	.026
3·DE	.600	.019	.933	.078
σ_e^2	.266	.015	.312	.024
σ_e^2	5.30	.096	6.52	.480
σ_u^2	.267	.008	.324	.020
$\sigma_e^2 + 3\cdot DE$.866	.015	1.25	.096

SD = Estimated standard deviation of the mean

Average of 4 trials/subject for subjects KC, HH, and WK

Average of 3 trials for subject WR

Tracking performance scores in analog-machine units

All scores in experimental units

The data obtained from subjects WK and WR were considered unsuitable for providing a meaningful test of the model for task interference, and no further analysis was performed on these results. WR's results were omitted because of the atypical performance of this subject on the decision task. Figure 12a shows that his 2-task decision score was fully twice that of any other subject, and his 1-task decision score was appreciably larger than that shown by any of the other six subjects who participated in this experimental program. (His 1-task score of 0.20 corresponded to an unreasonably large noise/signal ratio about -11 dB.)

The data from subject WK were also omitted from further consideration because of anomalous performance on the decision task. In particular, this subject's 1-task score was not self-consistent. Table 2 reveals that he achieved a decision error score of about 0.11 on this task in the first experiment; this score rose to 0.14 in this (the third) experiment, even with the benefit of additional practice on the 1-task decision situation. Thus, we do not know whether the very low level of task interference revealed by this subject's performance is a meaningful result, or whether it indicates that the subject was not working to full capacity when performing the decision task alone. The anomalous behavior of subjects WK and WR is discussed further in Chapter 5.

The model for simultaneous tracking and decision performance was tested against the data obtained from subjects KC and HH. The first step in this procedure was to select model parameters to match the 1-task decision and tracking performance of each subject. Decision performance was matched by using the curve of Figure C-1 to find the noise/signal ratios that corresponded to the decision error scores. Similarly, noise/signal ratios were chosen to provide perfect matches to the 1-task mean-squared

tracking error scores. Values for the time delay and motor noise parameters were selected on the basis of previous manual control studies (Refs. 6-10), and a lag time constant was selected to match the 1-task error-rate and control scores to within 10 percent. Numerical values for these parameters are given in Figure 13. This figure also shows the theoretical relationship between the various tracking performance measures and the noise/signal ratio.* Superimposed on these curves are the average 1-task scores for subjects KC and HH.

Table 6 shows the noise/signal ratios that were associated with 1-task decision and tracking performance. These ratios were considered to represent "full attention", and theoretical curves of task performance versus attention were obtained according to the procedure described in Section 3.4.2. All model parameters other than noise/signal ratio were held fixed for this analysis.

TABLE 6

NOISE/SIGNAL RATIOS CORRESPONDING TO "FULL ATTENTION"

Task	Subject	
	KC	HH
Decision	-20.6	-18.2
Tracking	-22.8	-20.8

Figure 14 shows the predicted 2-task performance scores for combined decision and tracking for subjects KC and HH. Total

*The theoretical relation between mean-squared tracking error and noise/signal ratio is shown on an expanded scale in Figure C-5 of Appendix C. In this appendix we discuss more fully our selection of values for model parameters.

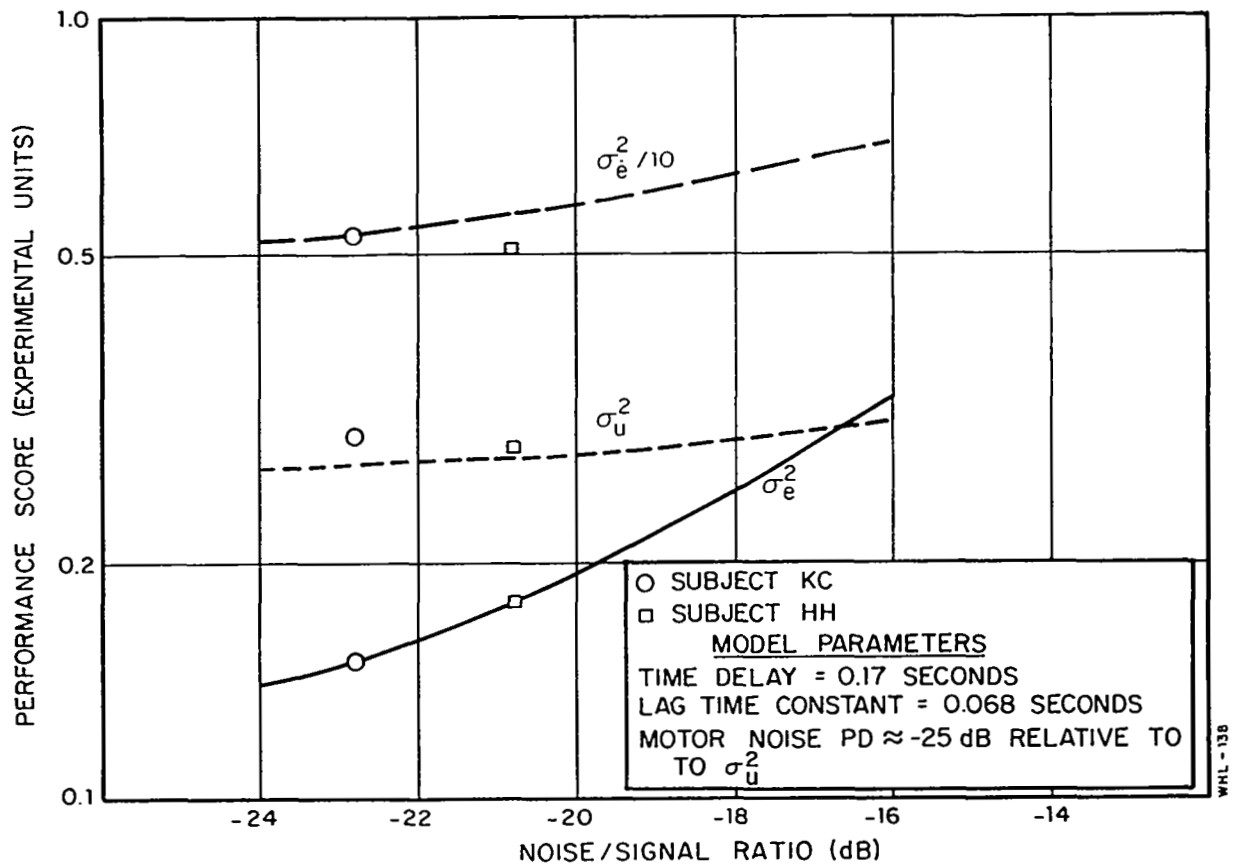


FIG. 13 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED TRACKING PERFORMANCE MEASURES

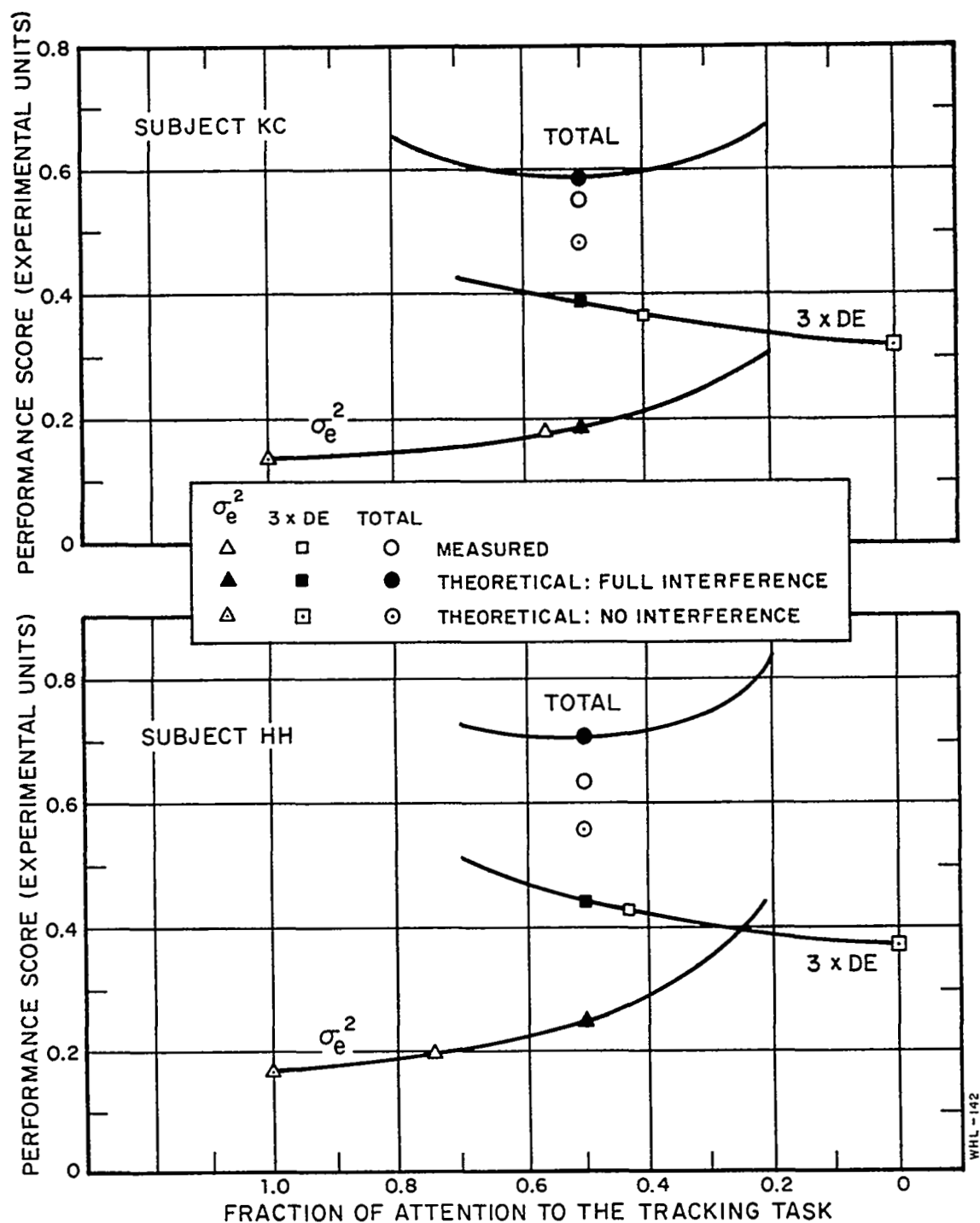


FIG. 14 EFFECT OF DIVISION OF ATTENTION ON DECISION, TRACKING, AND TOTAL PERFORMANCE SCORES

performance, tracking error, and weighted decision error scores are shown as a function of the fraction of attention paid to the tracking task. From this figure we predict that each subject should devote about half his attention to each task for optimal performance. We note, however, that total performance is relatively insensitive to attention in the vicinity of this theoretical optimum.

Superimposed on the theoretical curves in Figure 14 are the theoretical 2-task performance scores which correspond to no interference and to full interference. Also shown are the 2-task scores that were obtained experimentally. The "no interference" theoretical scores are simply the scores obtained in the 1-task experiments. (The no-interference total score is the weighted sum of the 1-task tracking and decision error scores.) The "full interference" scores are the ones predicted by our model for task interference. These scores are obtained from the theoretical curves of Figure 14 for a 50% allocation of attention to the tracking task (which is the allocation of attention that yields the lowest predicted total score).

Both subjects achieved 2-task total scores that fell between the theoretical scores associated with no interference and with full interference. Thus, the mutual interference between the tracking and decision tasks was not as severe as was predicted by the model. Whether or not the measured 2-task scores differ significantly in a statistical sense from either of the theoretical scores is questionable. T-tests performed on the data from either subject alone do not reveal differences significant at the 0.05 level. On the other hand, statistical significance is obtained if we pool the data of these two subjects (that is, if we treat the data as eight replications obtained from a single subject). T-tests then show that the average 2-task total performance score differs from the average no-interference score at the 0.01 level and from the average full-interference score at the 0.05 level.

Since we have reliable results from only two subjects, we cannot claim with a high degree of assurance that our model for interference either does or does not apply to the combined decision and control situation. There appears little question that interference does occur: all four subjects yielded higher total and component scores in the 2-task situation. The *degree* of interference remains in question. Accordingly, we must conclude at this stage that the model which we have proposed for combined decision-making and control shows promise, and that a conclusive set of experiments remains to be conducted.

We suspect that the inability to obtain reliable, conclusive data in this third experiment was due, in part, to the apparent insensitivity of the total performance score to attention. Note that we can predict the combined-task performance score to within 15 percent with either the full-interference or no-interference concept incorporated into the model. In order to obtain a more conclusive set of results, a task should be explored which is more sensitive to attention (i.e., more sensitive to the noise/signal parameter of the model). The problem of insensitivity to noise/signal ratio is discussed more fully in Chapter 5, and in Chapter 6 we suggest an experiment which may largely avoid this particular drawback.

5. DISCUSSION OF RESULTS

Agreement between theory and experiment was quite good for the situations involving only decision-making tasks. Decision error scores were predicted to within an accuracy of about 10 percent in both 1- and 2-task situations. Agreement was less good for the task of simultaneous decision-making and continuous control, with prediction errors on the order of 15 percent. Although the differences between predicted and measured performance scores were not large in an absolute sense, these differences cannot be entirely ascribed to "experimental variability."

We suspect that certain methodological problems associated with the experimental decision task contributed to the discrepancy between theory and experiment. These problems are discussed below. In the subsequent section of this chapter, we suggest two refinements to the model which might improve the predictive accuracy of the model.

5.1 Methodological Considerations

In order for us to explore the limitations of human psychomotor performance, we should, if possible, use an experimental task which is designed to motivate the subject to work to near-full capacity. Moreover, if the experimental results are to be meaningful, the task should be one for which the subject can readily learn the appropriate (i.e., optimal) response strategy. The particular decision task used in this study was somewhat deficient on both counts, as we shall show below.

If it were possible to obtain a describing function and remnant spectrum for the human's decision strategy, we could assess the relative importance of the motivational and learning problems. In the sense that "motivation" is reflected by the degree to which the human suppresses his internal noise, an indication of motivation could be obtained by a linear transformation of the remnant spectrum to an equivalent observation noise process. Comparison of theoretical and measured describing functions would reveal the extent to which the subject had learned the optimal strategy. Unfortunately, the intermittent nature of the subject's response precludes any such analysis; we can only speculate on the importance of these factors.

5.1.1 Insensitivity of Performance to Noise/Signal Ratio

Perhaps the most serious drawback of the decision task which we explored—at least with respect to testing the model—was the relative insensitivity of decision error to the human's noise/signal ratio. This insensitivity may be largely responsible for the wide range of noise/signal ratios needed to match all the single-task decision scores perfectly (Figure 9).

The human apparently attempts to suppress his internal noise to a greater extent as the sensitivity of performance to noise/signal ratio increases. In a study of manual control performed under an earlier NASA-ARC contract, we found that our pilots achieved noise/signal ratios on the order of -26 dB when tracking unstable second-order dynamics (Ref. 9). Earlier studies conducted with a variety of stable controlled-element dynamics had revealed noise/signal levels of about -20 dB (Refs. 4-8). Model analysis showed that the sensitivity of mean-squared

tracking error to noise/signal was considerably greater for the unstable dynamics than for the stable dynamics. Thus, the subjects were apparently willing to operate at an unusually low level of internal noise if the payoff was sufficient. Jex and Magdeleno have reported data which support this conclusion (Ref. 15).

The theoretical curves of Figure 4 show that the sensitivity of decision error with respect to the human's noise/signal ratio decreases as the task difficulty increases. For a doubling of the noise/signal ratio from -20 dB to -17 dB, the decision error for Task A increases about 17 percent, whereas an increase of only about 5 percent is observed for Task D.* (The same increase in noise/signal ratio corresponds to a 44 percent increase in mean-squared error for the K/s tracking task used in this study.) Thus, it is entirely possible that the subjects were insufficiently motivated to maintain a -20 dB noise/signal ratio when performing Task D.

Task-induced motivation may explain, in part, the tendency of the subjects to perform better than predicted in the combined decision and control task. One simple explanation of these results is that the subjects "worked harder" in the 2-task situation in this particular experiment. As a measure of how

*One would expect the sensitivity of decision error to the human's noise to decrease as the amount of simulated "instrument noise" is increased. Since the experimentally added noise was greatest for Task D, the proportion of total system noise attributable to the human was least. Thus, a given percentage increase in the human's noise represented a relatively lower percentage increase in total system noise for Task D than for the remaining decision tasks.

much harder the subjects worked, we can compute the amount of attention that the subjects devoted to each of the component tasks in the 2-task situation. Attention is defined as

$$ATTN = P^{(1)}/P^{(2)}$$

where $P^{(1)}$ and $P^{(2)}$ are the noise/signal ratios associated with the 1-task and 2-task performance measures, respectively. The noise/signal ratios, in turn, are derived from the error scores as described previously.

Levels of attention associated with 2-task performance are shown for subjects KC and HH in Table 7. The "total attention" levels given in this table are simply the summations of the attention levels associated with the component tasks. Also shown in Table 7 are the decision error and tracking error scores, along with the inferred noise/signal ratios, for the 1- and 2-task situations. From this table we observe that we can account for combined decision and tracking performance if we assume that subjects KC and HH increased their "attentional capacities" by 21 percent and 33 percent, respectively in the 2-task situation.

Now, we have shown that humans tend to lower their internal noise levels (which, we suggest, is equivalent to increasing the level of attention) as the sensitivity of performance to noise/signal ratio increases. Accordingly, let us compute the sensitivity of the total decision-plus-performance score with respect to noise/signal. In order to simplify the computation, we shall assume that a 50-percent division of attention between the two component tasks allows near-optimal performance. (See

TABLE 7

PERFORMANCE SCORES AND INFERRED LEVELS
OF ATTENTION FOR COMBINED DECISION AND CONTROL

Task	Variable	SUBJECT KC		SUBJECT HH	
		1-task	2-task	1-task	2-task
Control	σ^2e	.150	.186	.178	.202
	P(dB)	-22.8	-20.5	-20.8	-19.6
	ATTN	--	.59	--	.76
Decision	DE	.111	.123	.125	.143
	P(dB)	-20.6	-18.5	-18.2	-15.8
	ATTN	--	.62	--	.57
Total	ATTN	--	1.21	--	1.33

the theoretical curves of Figure 14.) Thus, a "full capacity" noise/signal ratio of -20 dB for the decision and tracking tasks performed separately implies ratios of -17 dB each of the two tasks when performed concurrently. A doubling of the full-capacity noise/signal ratio is represented by -14 dB on each task. Using the curves of Figures C-1 and C-5, we find that this increase in noise/signal ratio corresponds to an increase in total performance score of about 38 percent, where total performance is defined as the mean-squared tracking error plus three times the decision error. This fractional increment in performance score is about twice that which we predicted above for the decision task alone. Thus, it is reasonable to expect that the subjects were more strongly motivated to reduce their internal noise levels when performing the combined task

(or when performing a single tracking task) than when performing a single decision task.

5.1.2 Learning Difficulties

The subjects may have encountered difficulty in learning the strategies appropriate to the various decision tasks because of inadequate knowledge of results during the training period. The only knowledge of performance given to the subject was the decision error score that was told to him at the end of each training trial. Thus, if the subject were to try various strategies during the course of a single trial, he would not know which of the variations was best.

The difficulty in providing the subject with continuous feedback during the trial arises from the open-loop nature of the task. That is, the subject's response behavior has no influence on the signal shown on his display as it does, for example, when the subject is actually controlling the signal. Various methods of presenting relatively instantaneous knowledge of performance were considered (such as illuminating a light whenever the subject's response was incorrect). These ideas were rejected, however, because of the high probability that the subject would learn to respond to the performance indicator and not to the signal on the primary display. To some extent, then, the relatively large noise/signal ratio inferred for decision Task D may reflect an inappropriate estimation strategy on the part of the subject.

One of the subjects (WR) had a particularly severe learning problem. He did not lack for motivation; he appeared genuinely

concerned about the quality of his performance on the decision task. We attempted to improve his performance by providing detailed explanations of the task and of the appropriate strategy. Nevertheless, he was not able to bring his decision score down to a reasonable level, even with considerable practice. His tracking performance, on the other hand, was consistent with what we have seen in previous studies, so there is no reason to doubt that this subject possessed a reasonable amount of psychomotor skill. (He was, in fact, qualified as a private flight instructor and was the only subject participating in this study who had aircraft piloting experience.) Apparently, this subject was unable to learn the task effectively without continuous feedback of performance.

We do not have a good explanation for the performance of subject WK on the decision task. His 1-task decision score was appreciably higher in the third experiment (combined decision and control) than it had been for the same task in the first and second experiments. Allowing for the possibility that the subject had performed atypically on the day he performed the third experiment, we let him repeat this experiment. Before taking data a second time, however, we provided additional training to restore the subject's skill on the decision task. Nevertheless, the second replication of the combined decision and control experiment gave the same results as the first; namely, an unexpectedly high 1-task decision score. It is as though the subject either "forgot" the appropriate decision strategy or lost his motivation to perform well on the decision task alone in this particular experimental situation.

5.2 Model Refinements

5.2.1 Non-Constant Noise/Signal Ratio

We expected prior to the first experiment that a noise/signal ratio of about -20 dB would allow us to match the subjects' decision performance for a variety of decision tasks. This assumption was based on our success at matching human controller behavior with this noise level for a number of control situations involving stable controlled-element dynamics. Such was not the case, however, and we found an apparently linear relationship between the decision error and the logarithm of the noise/signal ratio.

In keeping with the previous discussion of these results, we suggest that the model might be improved by taking the sensitivity of performance to noise/signal ratio into account. That is, the rules for selecting observation noise levels might be modified to show the noise/signal ratio as an explicit function of this sensitivity. There is enough experimental evidence to indicate that this is a reasonable idea, although further study would be needed in order to determine with any degree of precision what this function should be. A model refinement of this sort would improve the predictive accuracy of models for manual control as well as for decision-making.

5.2.2 Time-Varying Observation Noise Process

In order to simplify the analysis of the decision task, we have treated observation noise as a time-stationary random process. This treatment is actually at variance with our assumption of an underlying multiplicative noise process. (See the analysis of observation noise in Appendix B.) To be consistent, we ought to

consider the power density level of the observation noise as a time-varying quantity which varies with the instantaneous magnitude of the observed signal.

The assumption of a time-stationary observation noise process has apparently worked very well for modelling human response behavior in continuous control situations. If one measures performance in terms of mean-squared tracking error, as we have done, then the effect of a given amount of estimation error on performance is independent of the instantaneous value of the tracking error. In this case, no loss of predictive accuracy results from consideration of average observation noise characteristics.

The relation between observation noise and decision performance is more complicated, at least for the type of decision task we have studied. The effect that a given amount of estimation error has on decision performance depends very much on the relation between the magnitude of the estimation error and the instantaneous value of the "signal." For example, if the "signal" is two target widths beyond the target boundary, the subject will make the correct decision even if the instantaneous error in his estimate of the signal position is substantial. On the other hand, relatively small estimation errors may cause an incorrect decision if the signal is very close to one of the target boundaries. A more accurate modelling procedure would take account of the relation between instantaneous signal value and the variance of the accompanying estimation error.

It is possible that the subjects took advantage of the time-varying characteristics of the observation noise when performing

simultaneous decision and tracking tasks. For example, they could have shared attention between the tasks when the decision signal was close to a target boundary and paid nearly full attention to the tracking task at other times. Such a strategy might yield better performance than that predicted by a model in which the division of attention is assumed constant for the duration of a trial. On the other hand, one would also expect a time-varying strategy of this sort to improve performance in the two-task decision situation. This apparently was not the case, however.

The only way to determine whether or not a time-varying observation noise process would account for the discrepancies between theory and experiment would be to incorporate this time-variation into the digital implementation of the model and perform the required model analysis. This modification to the model was not made, because the effort involved did not seem warranted in the context of this study.* Nevertheless, time-variations of this sort will probably have to be included in the model if more realistic situations are to be analyzed, since most decision-making tasks are intermittent, rather than continuous, in character.

*Time variations of a different type have already been incorporated into the pilot-vehicle model to allow analysis of the approach - to-landing problem. (Ref. 12).

6. CONCLUDING REMARKS

A model for human decision-making has been developed and tested against experimental data. This model is a straightforward adaptation of the optimal-control model for pilot/vehicle systems developed previously by BBN. The "optimal gain matrix" included in the pilot/vehicle model is replaced by an "optimal decision rule" in the decision model. Otherwise, the two models are quite similar: both include the concepts of time delay, observation noise, optimal prediction, and optimal estimation. The model for decision-making developed in this study is intended to apply to situations in which the human bases his decision on his estimate of the state of a linear plant.

Three experiments were conducted, the first of which allowed us to determine the extent to which the model could predict the effects of changes in task parameters on decision performance. The remaining two experiments provided tests of our model for interference in multiple-decision and in decision-plus-tracking situations. Experimental results agreed very closely with predicted performance in situations involving only decision-making. Using fixed values for human time delay and noise/signal ratio, we were able to predict both 1-task and 2-task average scores to within an accuracy of about 10 percent. Agreement was less good for the simultaneous decision and control situation, with prediction errors on the order of 15 percent. Discrepancies between theory and experiment could not be attributed entirely to experimental variability. Problems relating to the motivational aspects of the decision task and the difficulty in learning the optimal decision strategy were considered, along with suggestions for refining the model.

As we discovered after we had proceeded well along in this study, the very nature of the decision task made it difficult to obtain conclusive results. Most importantly, decision performance was found to be relatively insensitive to the amount of attention paid to the task by the pilot. Accordingly, we recommend that future attempts to validate the model for decision-making developed in this study be concerned with tasks for which the human's overall decision performance is sensitive to the details of his response behavior.

The pilot's task of deciding whether or not to land his aircraft is a decision problem to which the model may usefully be applied, and one which will allow a more critical test of the predictive accuracy of the model. Since the landing-decision task can be formulated as the task of deciding whether or not the aircraft is within the "landing window," this task falls within the class of those that can be handled by the model. Ideally, the model could be used to predict how changes in the nature of the information displayed to the pilot will help (or hinder) the pilot's decision-making ability. In addition, one could explore the effects of mutual interference between the decision task and the task of controlling the aircraft.

The landing-decision task, even when simulated in the laboratory, differs from the decision task explored in this study in some important respects. First of all, a realistic landing-decision task is multi-dimensional. The pilot must not only determine whether or not the aircraft's altitude is within an acceptable range, but he must also check on the lateral position, rate-of-descent, and possibly airspeed and attitude as well. Because of the complexity of the task, we suspect that decision performance will be reasonably sensitive to the pilot's internal noise (particularly in the absence of simulated instrument noise).

The pilot will generally not have the "target boundaries" displayed to him. Instead, he must compare his perception of the state of the vehicle against some ideal state that is stored in his memory. An additional source of estimation error is now introduced into the problem to the extent that the pilot's mental image of the target area fluctuates with time. One might treat this problem by associating observation noise processes with the target boundaries as well as with the display variables related to flight control. Experimentation and analysis will be necessary to determine whether or not this is a valid approach, and, if so, what noise levels should be associated with the pilot's mental image.

If a single individual is controlling the aircraft and making the decision with regard to landing, one must consider the possibility of interference between the control and decision tasks. Because the same information obtained from the same displays is used for both tasks, the current model for interference may not be applicable to this situation without modification. (At present, interference is assumed to occur among perceptual variables and is accounted for by appropriate changes in the noise/signal ratios associated with each variable.)

The model for decision-making might also be used to analyze the pilot's task of detecting and identifying changes in control system dynamics. System dynamics will often degrade markedly whenever a system failure occurs, or whenever the "operating point" of the vehicle changes because, say, a stall is imminent. The pilot must then identify the nature of the problem and adopt appropriate recovery strategy. The entire decision problem may be thought of as a four-step process: (a) detection of the change

in dynamics, (b) identification of the new dynamics, (c) modification of the pilot's basic control strategy, and (d) optimization, or "fine tuning" of the response. (See Reference 16 for a discussion of adaptive manual control.)

The model should be most readily applicable to the detection aspect of the problem. Elkind and Miller (Ref. 17) have developed a model for the detection task in which the human is assumed to estimate the system states and to detect a change if these states exceed some pre-determined limits. There is thus a close analogy between this detection task and the decision task which has been described in this report. Note that we would have to include the pilot's optimal control strategy in the model for the detection problem in order to account for the fact that the pilot closes the control loop.

We suspect that the model for decision and control could be applied to the identification phase of this decision problem if appropriate modifications were made to the model. This task is more complicated than the decision tasks we have considered up to now. It is no longer sufficient for the pilot to observe that system behavior is unusual; he must decide which set of events is most likely to account for this behavior. One way to model the pilot's decision strategy is to assume that he constructs a model of the system for each of the possible control system configurations that might occur. The pilot then compares the observed vehicle state with the outputs of each of the models and, using Bayesian decision rules, makes a guess as to how the system dynamics have changed (Ref. 17). In order to account for this decision strategy, the current model would have to be augmented to represent additional "internal models" of the flight-control system.

In conclusion, we submit that the model for decision-making and control described in this study is worthy of further consideration. With some additional research needed to refine and extend the model, it should prove applicable to the analysis of important decision-making problems which face pilots in flight-control situations. In particular, the model should prove useful in indicating the extent to which changes in the control and display systems will affect the pilot's decision-making capability.

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APPENDIX A

EXPERIMENTAL APPARATUS AND PROCEDURES

A.1 Principal Experimental Hardware

A.1.1 Computing Machinery

An Applied Dynamics AD/4 Analog-Hybrid System was used to simulate vehicle dynamics, filter input signals, generate the display, and compute the various performance measures. Input signals were obtained from pre-recorded analog magnetic tape.

A.1.2 Subject Booth

Displays and controls were located in a subject booth that was isolated both acoustically and visually. A chin rest was provided to maintain a fixed eye-to-display distance.

A.1.3 Display

The subject was provided with an oscilloscopic presentation of the display shown in Figure A-1. Eye-to-display distance was about 70 centimeters; thus, 1 cm. of display displacement corresponded to approximately 35 milliradians (2 degrees) visual arc. Target boundaries were generated electronically and were located at ± 18 millirad (± 1 degree) visual arc from the zero reference level. A zero reference indication was provided by a 0.16 cm strip of opaque Red tape during the final experiment to facilitate manual control performance. No grid lines were shown on the 'scope face. The phosphor of the display tube was type P-11, which gave a bluish cast to the reference and error indicators.

A.1.4 Controls

A single-throw spring-return pushbutton allowed the subject to indicate his instantaneous "decision." The pushbutton was mounted

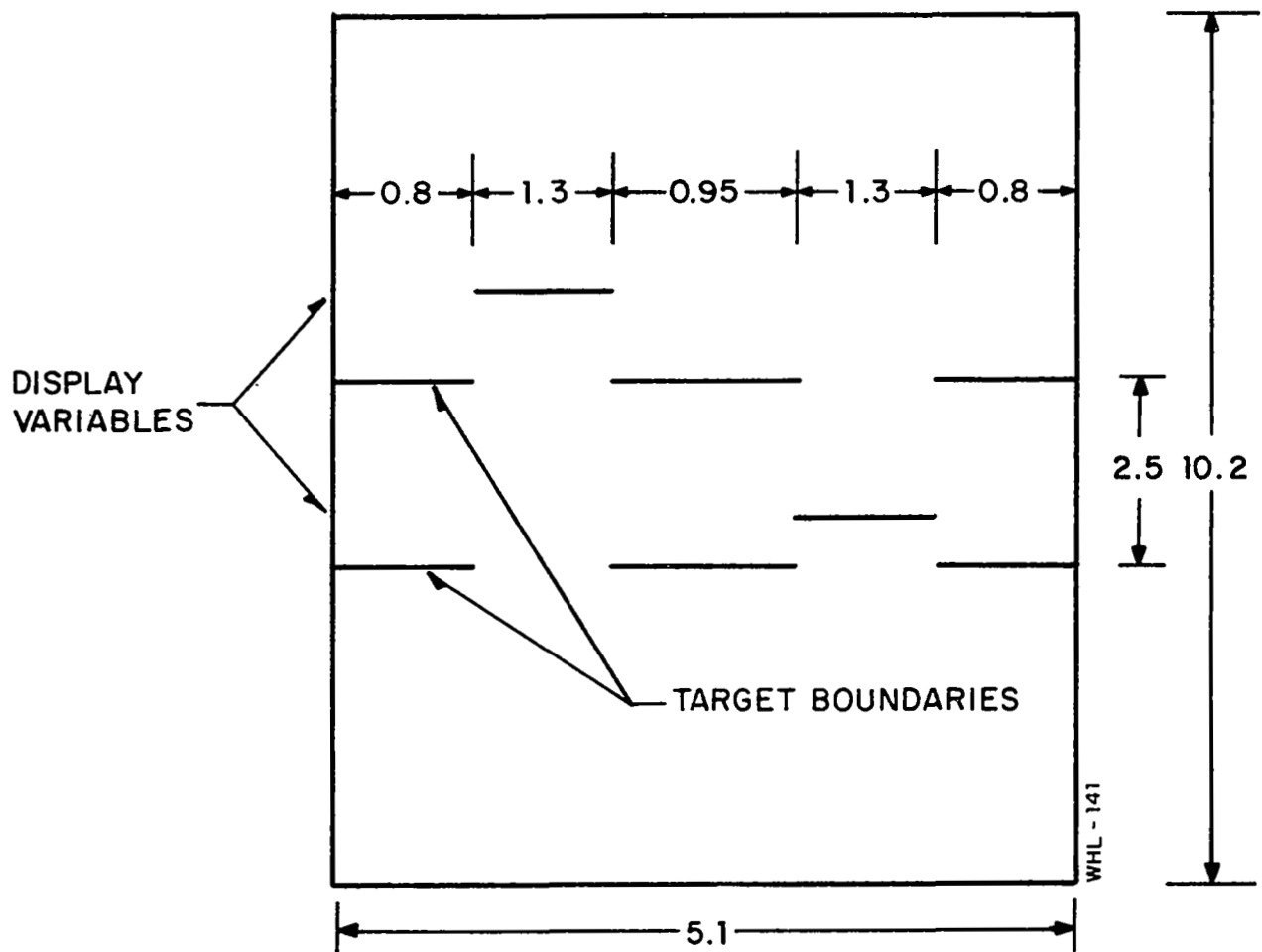


FIG. A-1 DISPLAY FORMAT

Dimensions shown in centimeters.

Not drawn to scale.

so that it could be hand-held and thumb-operated. The subject was instructed to keep the pushbutton depressed whenever he thought the "signal" was within the target area; otherwise, he was to release it.

An aluminum stick attached to a force-sensitive hand control (Measurement Systems Hand Control, Model 435) allowed the subject to control the tracking variable. The stick-control combination provided an omnidirectional spring restraint with a restoring force of about 28 newtons per centimeter deflection of the tip of the stick. The subject used wrist and finger motions to manipulate the control stick and was provided with an armrest to support his forearm. The stick was mounted vertically; forward deflection of the stick imparted an upward velocity to the tracking error signal that was proportional to the applied force.

A.2 Subjects and Training Procedures

A.2.1 Experimental Subjects

Seven subjects participated in various phases of the experimental program. Six of these subjects were current or recent engineering students at Massachusetts Institute of Technology with no flight experience and no experience with laboratory tasks of the type explored in this study. The remaining subject was a former private flight instructor who had participated in previous studies of manual control.

A.2.2 Run Length

All training and data trials lasted four minutes and were generally presented in sessions of two or three trials each with a minimum rest period of about 10 minutes between sessions. Minimum rest periods of 1 minute were provided between successive trials within a session.

A.2.3 Inputs

A number of input signals were used in succession during training to minimize learning of the input. A separate set of four input segments were reserved for data-taking. In order to minimize the effects of input differences on the experimental results, the same input segment was generally repeated for each of the three conditions investigated during a data session.

A.2.4 Training on the Decision Task

The first training trial consisted of a run in which the subject simultaneously observed the "signal-plus-noise" variable $y(t)$ on one indicator and the "signal" $s(t)$ on the other indicator. The object of this trial was to enable the subject to learn the statistical properties of the "signal" and "noise" processes. For most of the subjects, a single trial of this sort was sufficient. Training then proceeded with only the signal $y(t)$ shown on the display, and the subject was informed of his "decision error" (defined below) at the end of each run.

The subjects appeared to reach a stable level of performance after a few training trials. That is, the decision error score did not exhibit a consistent decrease with practice. Accordingly, when training the subjects for the first experiment, we provided them with an equal number of training trials per task; we did not attempt to train to an asymptotic level of performance as we would normally do for a tracking task. Six trials per task were provided.

The subjects were trained to an apparently asymptotic level of performance prior to data-taking in the two-task decision situation. An average of 6 training trials on the two-task situation were conducted per subject.

When performing a single decision task, the subjects were instructed to minimize the total decision error (defined as the fraction of time during the run that their response was in error). This error score was computed as the sum of the two component error scores: (a) the "false-alarm" rate, defined as the fraction of time that the subject responded "in" when the signal was outside the target, and (b) the "miss" rate, defined as the opposite type of decision error. The subject was not told specifically how to apportion his total decision error among the component scores, and he was generally not informed of these component scores. If these two scores differed by more than a factor of two or three, however, the subject was informed of this and encouraged to reduce the bias in his decision criterion.

When performing two decision tasks concurrently, the subjects were required to minimize a composite score defined as the sum of the total decision error scores on each task. At the end of each run, they were informed of the composite score, plus the decision error associated with each task. They were not told how each decision error resolved into false-alarm and miss rates.

A.2.5 Training on the Tracking Task

Each subject was trained on the tracking task alone until an apparently stable performance level was reached. The instructions were to minimize mean-squared tracking error. Approximately 30 training trials were provided each subject.

The subjects were then trained to an apparently asymptotic level of performance on the combined decision-plus-tracking task (about 14 trials per subject). The subjects were instructed to minimize a weighted sum of tracking and decision errors. Before training was begun on the combined task, model analysis was

performed with nominal pilot parameters to determine a weighting on the decision task that would allow the decision and tracking scores to contribute roughly equally to the total performance measure. This weighting remained constant during the entire training and data-taking period. At the end of each session, the subject was informed of his total performance score, his tracking score, and his decision error score (both weighted and unweighted). The subject was not instructed as to how to apportion his total score among the component scores.

APPENDIX B

ANALYSIS TECHNIQUES

B.1 Revised Model for Observation Noise

The model for observation noise that we have used in the past is based on the assumption that pilot randomness arises from an underlying multiplicative noise process. We justify this assumption on the wealth of psychophysical evidence which shows that the human's errors in estimating various quantities tend to scale with the magnitudes of these quantities. In most of the tracking situations that we have explored in the past, the human's perceptual task has been to estimate the magnitude of system error and error rate with respect to a zero reference. For situations in which the signals have had zero means, we have considered the power density level of the observation noise process to be proportional to signal variance.

The perceptual task is somewhat different for the decision task that we have explored in this study. Here the subject's task is to determine whether or not the signal is on one side or the other of a target boundary -- not how far it is from a null value. Thus, the reference level is nonzero, and our analysis should take this into account.

In order to analyze the observation noise process in this task situation, let us start with our basic assumption of a multiplicative white noise process. We postulate the following model:

$$v_y(t) = [y(t) - Y_0] \cdot m(t) \quad (B-1)$$

where $y(t)$ is the signal displayed to the human, Y_0 is a reference level, $m(t)$ is a white noise process which might be associated with noise in the human's central processing mechanism, and $v_y(t)$ is the white noise process that is effectively added to the displayed variable. (We neglect the effects of visual resolution limitations, which would add another term to the model.) A separate and linearly independent noise process is associated with each of the perceptual variables to be estimated by the human. In general, the human will want to estimate the relative displacement and velocity of each display indicator.

The autocorrelation of the noise process $v_y(t)$ is defined as follows:

$$\begin{aligned}\phi_{vv}(t, \tau) &= \mathcal{E}\{v_y(t) \cdot v_y(t+\tau)\} \\ &= \mathcal{E}\{(y(t)-Y_0)(y(t+\tau)-Y_0)m(t) \cdot m(t+\tau)\} \quad (B-2)\end{aligned}$$

Since the multiplicative process $m(t)$ is assumed to be linearly independent of the display variable $y(t)$, the above expression may be written as a product of the autocorrelation of $[y(t)-Y_0]$ times the autocorrelation of $m(t)$. Since $m(t)$ is a white noise process, its autocorrelation function is zero for all nonzero values of τ , and it has a value of πP for $\tau=0$, where P is the power density level of $m(t)$ (defined over positive frequencies only).^{*} The above expression thus simplifies to

$$\phi_{vv}(t, \tau) = \mathcal{E}\{y(t)y(t+\tau)-Y_0(y(t)+y(t+\tau)) + Y_0^2\} \cdot \pi P \delta(\tau) \quad (B-3)$$

^{*}The power density level P has been referred to in the text as the pilot's "noise/signal ratio."

This autocorrelation function has nonzero value only for $\tau=0$. Thus, $v(t)$ is also a white noise process whose power density level is defined as

$$V_y(t) \equiv [\phi_{vv}(t,0)]/\pi \quad (B-4)$$

Since the expected value of a sum of terms is equivalent to the sum of the expected values for each term, we obtain

$$V_y(t) = \left[\mathcal{E}\{y^2(t)\} - 2Y_0 \mathcal{E}\{y(t)\} + \mathcal{E}\{Y_0^2\} \right] \cdot P \quad (B-5)$$

The above expression shows the power density level of the observation noise process as a time-varying function. That is, the expected noise power fluctuates with the moment-to-moment displacement of $y(t)$ from its reference value Y_0 . In order to simplify our analysis, we shall henceforth consider the time-average value of the noise power, which we denote simply as V_y . This simplified representation of observation noise has been adequate to account for pilot remnant in a variety of steady-state control situations.

For the particular decision task we have considered, analysis of the observation noise associated with indicator displacement is complicated by the presence of two reference levels ($+Y_T$ and $-Y_T$, the upper and lower target boundaries). We must make certain assumptions as to how the subject uses these reference levels in his estimation process. Let us assume that the subject's perceptual task is to estimate the distance of the display variable $y(t)$ from the target boundary which is closest at any instant of time. (This makes perfectly good sense when $y(t)$ is relatively close to one or the other target boundaries — the situation in which a decision error is most likely to occur.) Accordingly, the model of Equation (B-1) is modified as follows:

$$\left. \begin{aligned} v_y(t) &= [y(t) - Y_T] \cdot m(t) & y(t) > 0 \\ v_y(t) &= [y(t) + Y_T] \cdot m(t) & y(t) < 0 \end{aligned} \right\} \quad (B-6)$$

The expression for the power density level $V_y(t)$ is modified in a similar manner.

Let us compute the power density for the situation in which $y(t) \geq 0$. Equation (B-5) is written as

$$V_y^+ = \left[\int_0^{\infty} y^2 p(y) dy - 2Y_T \int_0^{\infty} y \cdot p(y) dy + Y_T^2 \int_0^{\infty} p(y) dy \right] \cdot P \quad (B-7)$$

where $p(y)$ is the probability density function of the display variable $y(t)$. For the decision task we are considering, $y(t)$ is a Gaussian random variable with zero mean and a variance σ_y^2 . Accordingly, we obtain

$$V_y^+ = \left[\frac{\sigma_y^2}{2} - 2Y_T (.3989) \sigma_y + \frac{Y_T^2}{2} \right] P \quad (B-8)$$

An identical expression is found for the noise associated with the time for which $y(t) < 0$. The total average noise power is given as the sum of V_y^+ and V_y^- and is approximately

$$V_y = [\sigma_y^2 + Y_T^2 - (1.6) Y_T \cdot \sigma_y^2] P \quad (B-9)$$

This expression applies to the estimation of indicator displacement. Since the reference for estimating indicator velocity is simply zero velocity, the power density level for observation noise on velocity is

$$V_y = \sigma_y^2 P \quad (B-10)$$

which is the model we have used successfully in the past.

The expression of Equation (B-9) may be written so as to indicate a "correction factor" to the simplified expression for observation noise. Thus,

$$V_y = \sigma_y^2 \cdot P \cdot C \quad (B-11)$$

where

$$C = 1 + \frac{Y_T^2}{\sigma_y^2} - (1.6) \frac{Y_T}{\sigma_y} \quad (B-12)$$

Correction factors appropriate to the four decision tasks investigated in this study are shown in Table B-1.

TABLE B-1
CORRECTION FACTORS APPLIED TO THE PILOT'S NOISE/SIGNAL RATIO

Configuration	σ_s/Y_T	σ_n/Y_T	σ_v/Y_T	Correction Factor (dB)
A	1.46	.197	1.47	-4.3
B	1.46	.311	1.49	-4.2
C	1.46	.311	1.49	-4.2
D	1.46	.623	1.59	-4.1

B.2 Prediction of Decision Performance

Descriptions of the experimental decision task and of the model for the human in this situation have been given in Chapter 3. In this section we elaborate on the analytical procedures for predicting decision performance. For convenience, the model structure shown in Figure 3 is repeated in Figure B-1.

B.2.1 Optimal Estimation

The portion of the model relating to optimal estimation allows us to predict the variances of the subject's best estimate of each state variable and the variances of the corresponding estimation errors. The variances corresponding to the estimate of the "signal" $s(t)$ and the error in estimating this signal $[s_e(t)]$ are then used to compute the subject's decision error, as described below. This portion of the model is contained in our optimal-control model for pilot/vehicle analysis, which has been fully described in the literature. The reader is referred to References 4 and 5 for further details.

B.2.2 Probability of Decision Error

In order to have a theoretical prediction to test against the experimental measure of decision performance, we must identify the relative frequency of an error with the "pure probability" of an error. Our experimental measure is, by necessity, a relative-frequency measure; that is, the decision error that we measure experimentally is defined as the fraction of time during a trial that the subject's response is incorrect. Our theoretical prediction, on the other hand, is the probability that, at any arbitrary instant of time, a decision error will be made.

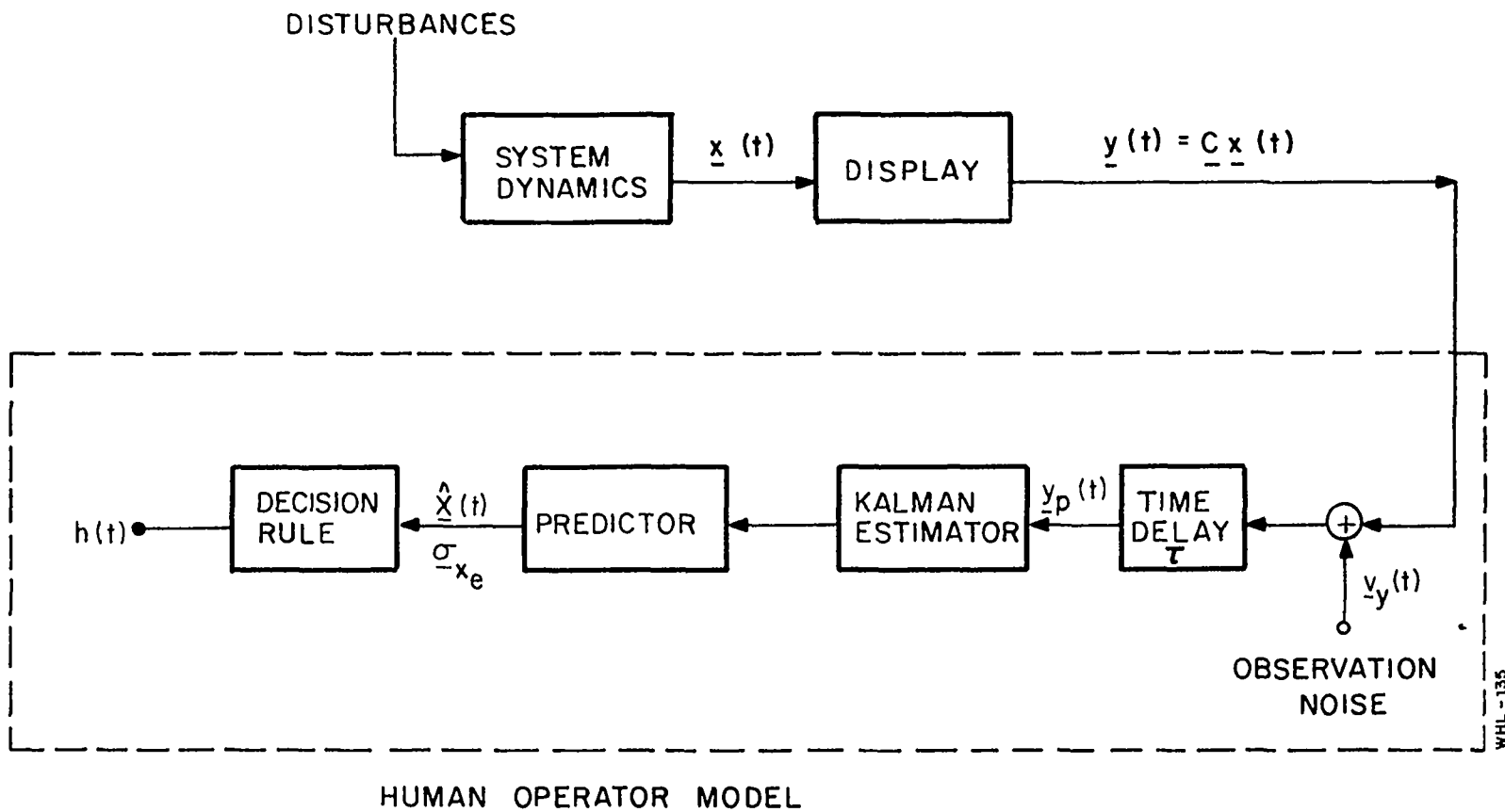


FIG. B-1 MODEL FOR THE DECISION TASK

Let us represent the various "states of the world" and the human's "decisions" by the following notation:

h_1 implies $s(t)$ within target area

h_0 implies $s(t)$ outside target area

H_1 implies a decision that $s(t)$ is within target area

H_0 implies a decision that $s(t)$ is outside target area

Two types of decision error may be made. A "false alarm," denoted by the condition (H_1, h_0) , occurs whenever the subject indicates "in" when, in fact, the signal is actually outside the target area. The reverse type of decision error, or a "miss", is denoted as (H_0, h_1) . The total probability of a decision error is the sum of the probabilities of a false alarm and of a miss. Thus,

$$P(DE) = P(H_1, h_0) + P(H_0, h_1) \quad (B-13)$$

We shall first compute the probability of a false alarm. Let $\pm Y_T$ be the target boundaries, $[s]$ be the location of the "signal" at any instant of time, $[\hat{s}]$ be the subject's best estimate of the signal, and $[s_e]$ be the estimation error. By definition,

$$s_e \doteq \hat{s} - s \quad (B-14)$$

We have already shown that the subject's strategy will be to respond "in" whenever his best estimate of the signal lies within his "decision boundary," denoted by $\pm Y_D$ (see section 3.3.2). The probability of a false alarm is thus

$$P(H_1, h_0) = P(|\hat{s}| \leq Y_D, |s| > Y_T) \quad (B-15)$$

The above expression can be simplified somewhat if we take advantage of the symmetry of the particular decision task that we have explored. Since the signal $s(t)$ and the noise $n(t)$ are each Gaussian random variables with zero means, the probability of a decision error being made when the signal is above the upper target boundary is equal to the probability of an error when $s(t)$ is below the lower boundary. Thus, the probability of a false alarm may be written as

$$P(H_1, h_0) = 2 \cdot P(|\hat{s}| \leq Y_D, s > Y_T) \quad (B-16)$$

The computation of this probability is facilitated if it is re-stated in terms of $[\hat{s}]$ and $[s_e]$. Using the definition of Equation (B-14), we derive the following identity: $s > Y_T$ implies that $s_e < \hat{s} - Y_T$. Equation (B-16) may now be written as

$$\begin{aligned} P(H_1, h_0) &= 2 \cdot P(-Y_D \leq \hat{s} \leq Y_D, s_e < \hat{s} - Y_T) \\ &= 2 \cdot \int_{-Y_D}^{+Y_D} \int_{-\infty}^{\hat{s} - Y_T} p(\hat{s}, s_e) \cdot ds_e \cdot d\hat{s} \end{aligned} \quad (B-17)$$

where $p(s, s_e)$ is the joint Gaussian probability density function for the signals s and s_e . Since the optimal estimate and estimation error predicted by the Kalman filter are linearly independent (Refs. 13,14), the joint probability density may be factored into the product of the individual densities. Thus,

$$P(H_1, h_0) = 2 \cdot \int_{-Y_D}^{+Y_D} \left[\int_{-\infty}^{\hat{s} - Y_T} p(s_e) \cdot ds_e \right] p(\hat{s}) \cdot d\hat{s} \quad (B-18)$$

The variables $[\hat{s}]$ and $[s_e]$ are Gaussian with variances $\sigma_{\hat{s}}^2$ and $\sigma_{s_e}^2$, respectively. Let us make the following change of variables:

$$\left. \begin{aligned} \xi_s &= \hat{s}/\sigma_s \\ \xi_e &= s_e/\sigma_{s_e} \end{aligned} \right\} \quad (B-19)$$

where ξ_s and ξ_e are normalized Gaussian variables. The probability of a false alarm may now be written as

$$P(H_1, h_0) = 2 \cdot \int_{-Y_D/\sigma_{\hat{s}}}^{+Y_D/\sigma_{\hat{s}}} \left[\int_{-\infty}^{\frac{\xi_s \cdot \sigma_{\hat{s}} - Y_T}{\sigma_{s_e}}} p_o(\xi_e) d\xi_e \right] p_o(\xi_s) \cdot d\xi_s \quad (B-20)$$

where $p_o(\xi)$ is the unit-variance Gaussian probability density function.

The probability of a "miss" is computed in a similar manner. This probability may be written as

$$\left. \begin{aligned} P(H_0, h_1) &= P(|\hat{s}| > Y_D, |s| \leq Y_T) \\ &= 2 \cdot P(\hat{s} > Y_D, \hat{s} - Y_T \leq s_e \leq \hat{s} + Y_T) \\ &= 2 \cdot \int_{Y_D}^{\infty} \left[\int_{\hat{s} - Y_T}^{\hat{s} + Y_T} p(s_e) ds_e \right] p(\hat{s}) \cdot d\hat{s} \end{aligned} \right\} \quad (B-21)$$

Making the change of variables shown in Equation (B-19), the probability for a miss may be written as

$$P(H_0, h_1) = 2 \cdot \int_{Y_D/\sigma_s}^{\infty} \left[\int_{\frac{\xi_s \cdot \sigma_s - Y_T}{\sigma_{s_e}}}^{\frac{\xi_s \cdot \sigma_s + Y_T}{\sigma_{s_e}}} p_o(\xi_e) d\xi_e \right] p_o(\xi_s) d\xi_s \quad (B-22)$$

The total probability of a decision error, $P(DE)$, is simply the sum of the probabilities shown in Equations (B-20) and (B-22). This number is a function of the target boundary Y_T , the decision level Y_D , and the variances of the subject's estimate of $s(t)$ and of his estimation error. These variances are given by the portion of the model relating to optimal estimation. The target boundary, Y_T , is an experimental parameter. The remaining parameter, Y_D , is the decision level that is selected by the subject to minimize his total decision score $P(DE)$.

It may be possible to solve analytically for the decision level which minimizes the decision score. Rather than attempt that, however, we have performed a numerical investigation of the relation between decision score and Y_D . For the condition in which $s(t)$ is equally likely to be inside or outside the target and decision errors of either type are weighted equally in the overall performance measure, the optimal decision boundary appears to coincide with the target boundary.

APPENDIX C

SUPPLEMENTAL THEORETICAL DATA

This appendix contains five graphs which relate predicted system performance to noise/signal ratio. Figures C-1 through C-4 pertain to performance on the four decision tasks explored in the first experiment; Figure C-5 pertains to mean-squared tracking error.

Values for the time delay and motor noise parameters of the model for the human controller were chosen on the basis of previous studies of manual control. A time delay of 0.17 second was selected because it was found to be typical of effective time delays measured in K/s tracking tasks (Refs. 8 and 9). (The time delay of 0.2 second assumed for decision-making represents an average delay that is typical of a wider range of manual control situations.) A motor noise/signal ratio of -25 dB was found to be representative of single-loop tracking behavior (Ref. 4).

Observation noise/signal ratios and effective lag time constants were selected to provide a good match to the mean-squared error, error rate, and control scores. The lag time constant of 0.068 second that was needed to match the tracking performance of subjects KC and HH was less than the time constants that we have generally found in previous experiments with K/s dynamics. (Time constants in the range of 0.08 to 0.1 are typical.) Since the subjects used in these experiments had no piloting experience, it is possible that they were less inhibited about making rapid control movements than were the subjects used in previous studies (who, for the most part, were instrument-rated pilots).

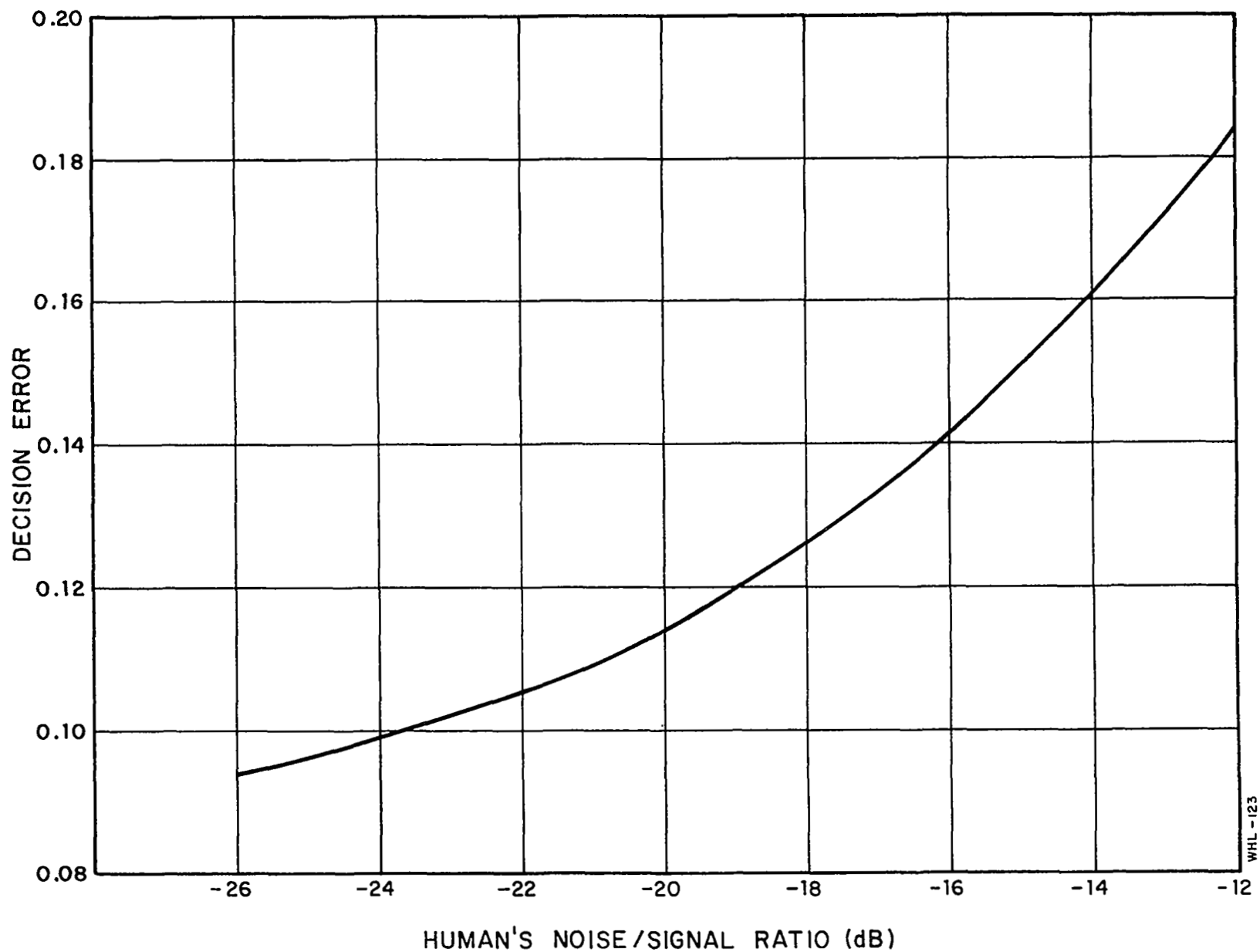


FIG. C-1 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED DECISION ERROR: TASK A

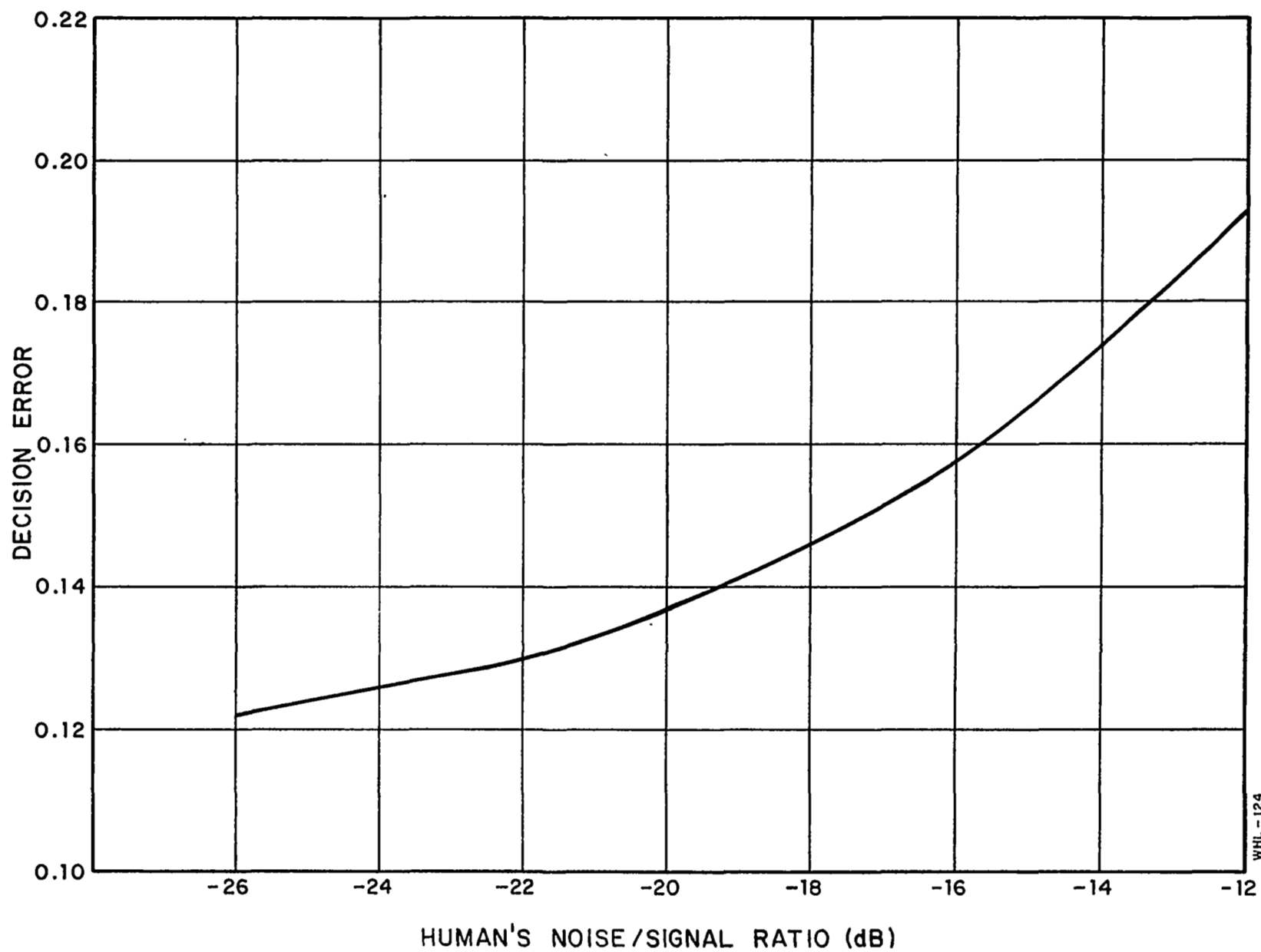


FIG. C-2 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED DECISION ERROR: TASK B

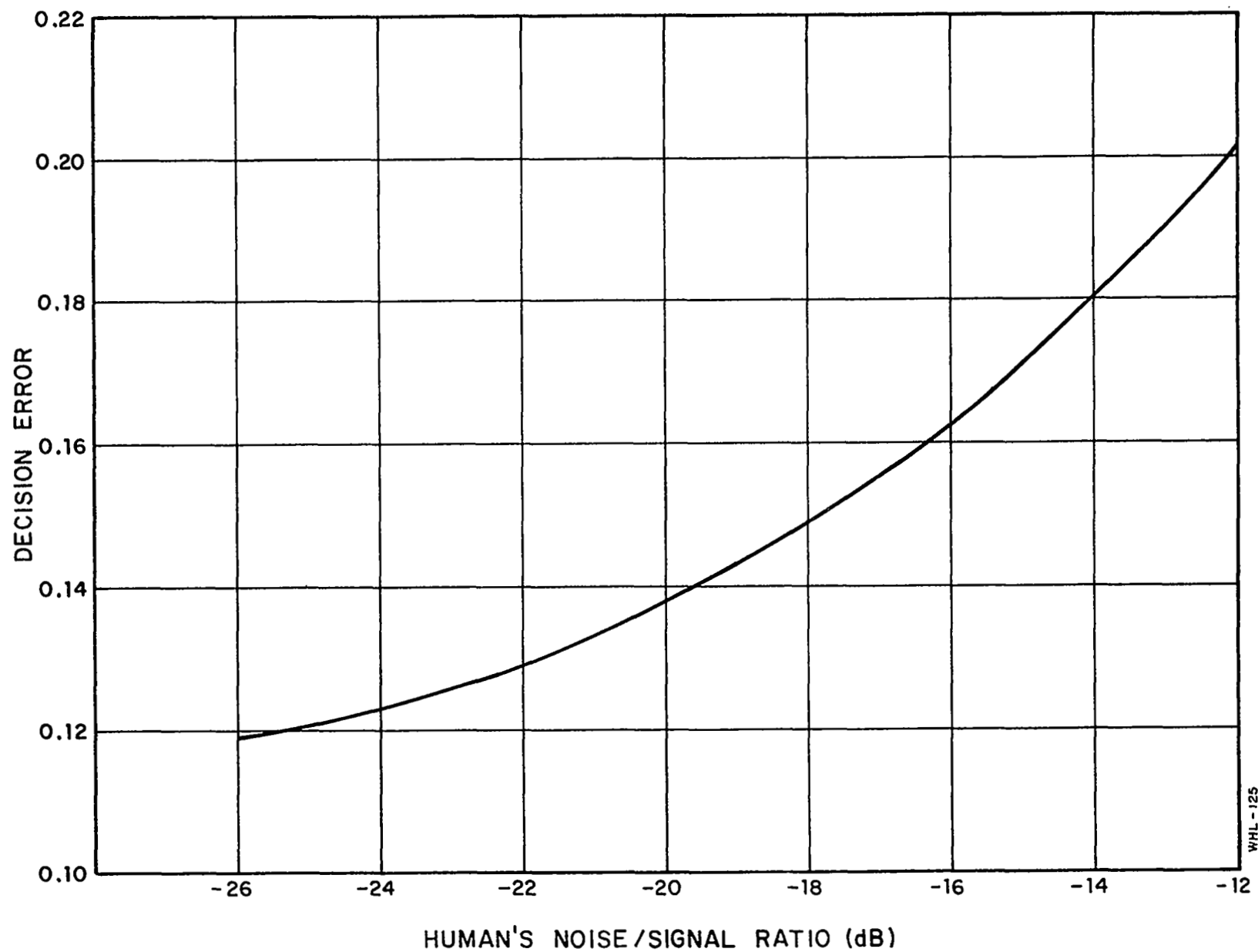


FIG. C-3 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED DECISION ERROR: TASK C

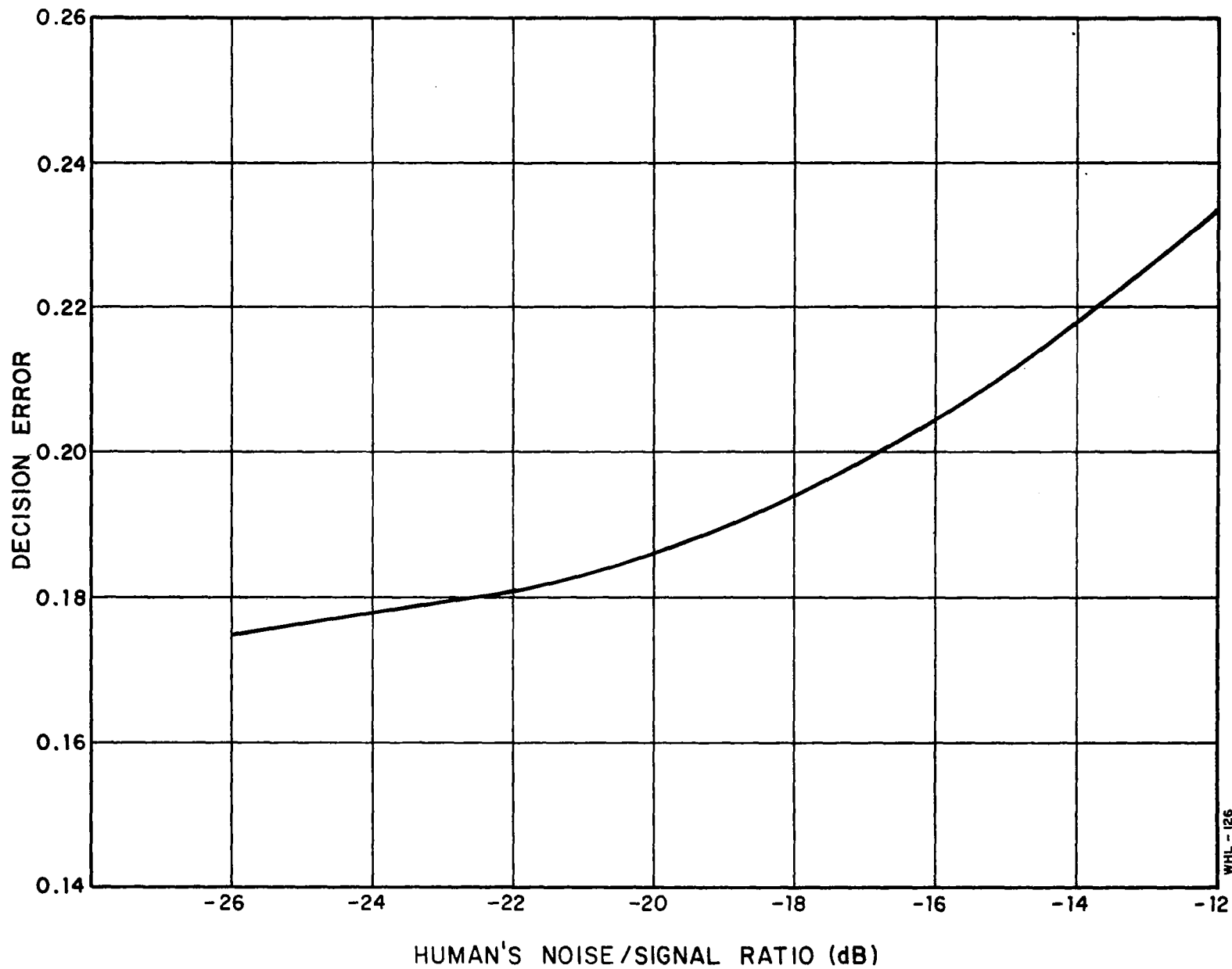


FIG. C-4 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED DECISION ERROR: TASK D

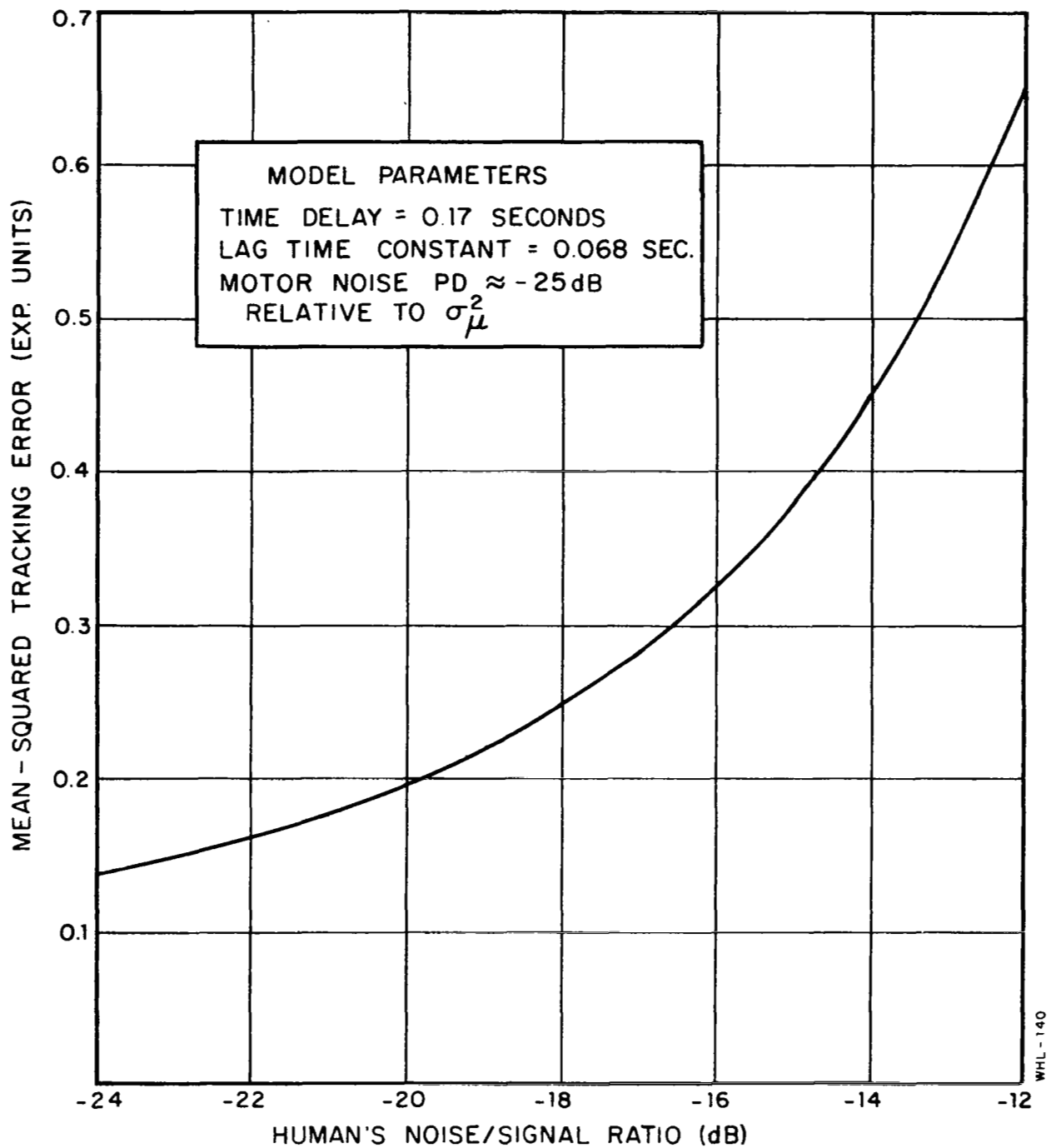


FIG. C-5 EFFECT OF NOISE/SIGNAL RATIO ON PREDICTED MEAN-SQUARED TRACKING ERROR

APPENDIX D

LIST OF SYMBOLS

<u>A</u>	Matrix of constants which represents system dynamics
C	Correction function for observation noise
<u>C</u>	Matrix of constants which relates display vector to state vector
DE	Decision error
F(s)	Filter characteristics
f	Fraction of attention
H	Subject's decision as to the state of the world
h	Assumed "state of the world"
J	Total performance score
m	Multiplicative noise process
n	"Noise" portion of signal-plus-noise variable displayed to the human
P	Human's noise/signal ratio. Also, probability density function
P _o	Noise/signal ratio pertinent to a single-task situation
s	The "signal" portion of the signal-plus-noise variable displayed to the human. Also, the Laplace operator.
\hat{s}	Human's best estimate of the "signal"
s _e	Error in estimation of the "signal"
U	Utility of a decision
v _u	Motor noise process
\underline{v}_y	Equivalent (vector) observation noise process
\underline{V}_y	Power density level of observation noise process
<u>w</u>	Vector of system forcing functions
<u>x</u>	Vector of state variables

\hat{x}	The human's best estimate of the state vector
y	Vector of display variables
y_p	Vector of display variables as perceived by the human
Y_D	Decision boundary adopted by human when performing decision task
Y_T	Target boundary used in decision task
z	Represents data base on which human bases his decision
δ	Impulse function
ω_0	Critical frequency of a noise-shaping filter
ϕ	Autocorrelation function
σ^2	Signal variance
τ	Human's effective time delay
τ_n	Lag time constant which appears in model for human controller
ξ	Normalized Gaussian variable
$-l^*$	Optimal gain matrix which appears in the model for the human controller

Subscripts

D	refers to decision boundary; also refers to decision task
e	refers to estimation error; also refers to tracking error
T	refers to target boundary; also refers to tracking task
u	refers to control signal
x	refers to system states
y	refers to display variables
1	refers to "signal" within target area; also refers to single-task situation
0	refers to "signal" outside target area

Superscripts

- M refers to multiple-task situation
- 1 refers to 1-task situation
- 2 refers to 2-task situation